THESIS FOR THE DEGREE OF DOCTOR OF PHILOSOPHY

# Computational driver behavior models for vehicle safety applications

From routine driving to safety-critical evasive maneuvers

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Cover image:
Driving phases depicted on a timeline from routine driving through critical situations to crash and post-crash. For each phase, the driver behavior aspects considered in this thesis are highlighted with symbols: steering (steering wheel), braking (brake pedal), and visual attention (eyes).

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*To my fantastic children*
*Alva, Signe, and Vidar*

*To my beloved Eric*

# Abstract

The aim of this thesis is to investigate how human driving behaviors can be formally described in mathematical models intended for online personalization of advanced driver assistance systems (ADAS) or offline virtual safety evaluations. Both longitudinal (braking) and lateral (steering) behaviors in routine driving and emergencies are addressed. Special attention is paid to driver glance behavior in critical situations and the role of peripheral vision.

First, a hybrid framework based on autoregressive models with exogenous input (ARX-models) is employed to predict and classify driver control in real time. Two models are suggested, one targeting steering behavior and the other longitudinal control behavior. Although the predictive performance is unsatisfactory, both models can distinguish between different driving styles.

Moreover, a basic model for drivers' brake initiation and modulation in critical longitudinal situations (specifically for rear-end conflicts) is constructed. The model is based on a conceptual framework of noisy evidence accumulation and predictive processing. Several model extensions related to gaze behavior are also proposed and successfully fitted to real-world crashes and near-crashes. The influence of gaze direction is further explored in a driving simulator study, showing glance response times to be independent of the glance's visual eccentricity, while brake response times increase for larger gaze angles, as does the rate of missed target detections.

Finally, the potential of a set of metrics to quantify subjectively perceived risk in lane departure situations to explain drivers' recovery steering maneuvers was investigated. The most influential factors were the relative yaw angle and splay angle error at steering initiation. Surprisingly, it was observed that drivers often initiated the recovery steering maneuver while looking off-road.

To sum up, the proposed models in this thesis facilitate the development of personalized ADASs and contribute to trustworthy virtual evaluations of current, future, and conceptual safety systems. The insights and ideas contribute to an enhanced, human-centric system development, verification, and validation process. In the long term, this will likely lead to improved vehicle safety and a reduced number of severe injuries and fatalities in traffic.



**Keywords:** Driver models, ADAS, safety benefit assessment, driver adaptation, visual attention, evidence accumulation, predictive processing, hybrid dynamical systems, PrARX.

# List of Publications

This thesis is based on the following publications[1]:

**Paper 1** Malin Sundbom, Paulo Falcone, and Jonas Sjöberg (2013), Online driver behavior classification using probabilistic ARX models. In *16th International IEEE Conference on Intelligent Transportation Systems (ITSC 2013)*, the Hague, the Netherlands, October 6–9, 2013, pp. 1107-1112.https://doi.org/10.1109/ITSC.2013.6728380

*Author contributions:* The author designed the driver model, parameter estimation method, performed the data analysis, and was the main author of the paper. She took part in designing the test track study but was not part of the data collection.

**Paper 2** Malin Sundbom and Jonas Sjöberg (2015), A study of appropriate model complexity for estimation of car-following behavior. In *3rd International Symposium on Future Active Safety Technology Toward zero traffic accidents 2015*, Gothenburg, Sweden, September 9–11, 2015.

*Author contributions:* The author designed the study and performed the analysis, with methodological support from the co-author, and was the main author of the paper. The data set used was provided from a previous study in which the author was not involved; thus, no data collection specifically targeting this paper was performed.

**Paper 3** Malin Svärd, Gustav Markkula, Johan Engström, Fredrik Granum, and Jonas Bärgman (2017), A quantitative driver model of pre-crash brake onset and control. In *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, October 9–13, 2017, Vol. 61, No. 1, pp. 339-343.https://doi.org/10.1177/1541931213601565

[1] The thesis author changed surname from Sundbom to Svärd in July 2015.

*Author contributions:* The author took part in the design of the suggested driver model, which was very much a group effort, and was the main author of the paper. She was also part of implementing the driver model in the simulation tool. The author was solely responsible for performing all included simulations and analyses.

**Paper 4** Malin Svärd, Gustav Markkula, Jonas Bärgman, and Trent Victor (2021),
Computational modeling of driver pre-crash brake response, with and without off-road glances: Parameterization using real-world crashes and near-crashes. *Accident Analysis & Prevention*, 163, Article 106433. https://doi.org/10.1016/j.aap.2020.105853

*Author contributions:* The author had a major role in the conceptualization of the paper and the design of the parameterization procedure, performed all the data analysis, and was the main author of this paper.

**Paper 5** Malin Svärd, Jonas Bärgman, and Trent Victor (2021),
Detection and response to critical lead vehicle deceleration events with peripheral vision: Glance response times are independent of visual eccentricity. *Accident Analysis & Prevention*, 150, Article 105853. https://doi.org/10.1016/j.aap.2021.106433

*Author contributions:* The author was the lead in the conceptualization of the paper and the design of the simulator study and distraction task, assisted in the implementation of the distraction task, performed the pilot study, took part in the data collection, performed the data analyses, and was the main author of this paper.

**Paper 6** Malin Svärd, Gustav Markkula, Mikael Ljung Aust, and Jonas Bärgman (*submitted*),
Using naturalistic and driving simulator data to model driver responses to unintentional lane departures. *Submitted for publication.*

*Author contributions:* The author conceptualized this paper, performed the data selection, carried out the analysis in its entirety, and was the main author. The data originated from three previous studies; thus, the author did not participate in any original study design or data collection.

Other publications by the author relevant to, but not included, in this thesis:

Malin Svärd, Jonas Bärgman, Gustav Markkula and Mikael Ljung Aust (2022), Do Car Drivers Respond Earlier to Close Lateral Motion Than to Looming? The Importance of Data Selection. In *12th International Conference on Methods and Techniques in Behavioral Research and 6th Seminar on Behavioral Methods, Vol 2*, held online, May 18–20, 2022.

*Summary:* This paper is based on data from the driving simulator experiment presented in Paper 5. The importance of post-hoc data selection in glance behavior studies which involve distraction tasks is demonstrated. Data selection strategies are suggested and applied to compare glance response times between a non-critical (but close) cut-in and a critical lead-vehicle deceleration.

Jonas Bärgman, Malin Svärd, Simon Lundell and Ahmed Shams El Din (2022), Validation of an eyes-off-road crash causation model for virtual safety assessment. In *Proceedings of the 8th international conference on Driver Distraction and Inattention*, Gothenburg, Sweden, October 18–19, 2022.

*Summary:* This paper demonstrates a novel crash-causation model based on a simple driver model and distributions of off-road glances. The model successfully reproduces the impact speed distribution of a set of real-world lead vehicle crashes.

# Acknowledgments

Never could I have imagined that day 12 years ago when this journey started, how much of a rollercoaster it would be. But hey, I liked the ride (even with the few unplanned stops along the way)! Many people have come and gone, and I owe so much to you all.

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This thesis would certainly not have been possible without the love and support of my family. My parents and sisters have always believed in me and supported me in all the difficult decisions I have had to make. To my children: Alva, Signe, and Vidar—you are my world! Thank you for being who you are, and I hope I will inspire you to never stop being curious.

Finally, my husband: Eric, I love you.

Malin Svärd, Gothenburg, March 2023

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The SHRP2 data set used in Papers 3, 4, and 6 was provided by the Virginia Tech Transportation Institute (VTTI) under a Data License Agreement[2,3]. The findings and conclusions of this thesis are those of the authors and do not necessarily represent the views of VTTI, the Transportation Research Board (TRB), or the National Academies.

The run-off-road dataset in Paper 6 was collected by the Swedish National Road and Transport Research Institute (VTI), funded by the Swedish excellence center Virtual Prototyping and Assessment by Simulation (ViP). Many thanks to Niklas Strand, Bruno Augusto, and Alexander Eriksson for providing the data. Thanks also to all involved in the EyesOnRoad field operational test.

At last, thank you to Kristina Mayberry for the excellent language reviews of this thesis and the appended Papers 4 and 6.

[2]SHRP2-DUL-16-172
[3]http://doi.org/10.15787/VTT1/WX2KSK
http://doi.org/10.15787/VTT1/OIQDNQ
http://doi.org/10.15787/VTT1/FQLUWZ

# Acronyms

| | | |
|---|---|---|
| ACC | – | Automatic Cruise Control |
| ACT-R | – | Adaptive Control of Thought – Rational |
| AD | – | Automatic Driving |
| ADAS | – | Advanced Driver Assistance Systems |
| AEB | – | Automatic Emergency Braking |
| AOI | – | Area Of Interest |
| ARX model | – | AutoRegressive model with eXogenous input |
| CZB | – | Comfort Zone Boundary |
| DMS | – | Driver Monitoring System |
| Euro NCAP | – | European New Car Assessment Programme |
| FCW | – | Forward Collision Warning |
| FFI | – | Fordonstrategisk Forskning och Innovation (Vehicle Strategic Research and Innovation) |
| FOT | – | Field Operational Test |
| GMM | – | Gaussian Mixture Model |
| HDS | – | Hybrid Dynamical System |
| HMM | – | Hidden Markov Model |
| HPD | – | Highest Posterior Density |
| IDM | – | Intelligent Driver Model |
| iTLC | – | Inverse Time to Lane Crossing |
| KdB risk index | – | Performance Index for Approach and Alienation |
| KDE | – | Kernel Density Estimation |
| LKS | – | Lane Keeping System |
| LM | – | Levenberg-Marquardt |
| MCMC | – | Markov Chain Monte Carlo |
| ML | – | Machine Learning |
| MLE | – | Maximum Likelihood Estimation |
| NDD | – | Naturalistic Driving Data |
| PCA | – | Principal Component Analysis |
| PEM | – | Prediction Error Method |
| PrARX model | – | Probabilistic AutoRegressive model with eXogenous input |
| PSO | – | Particle Swarm Optimization |

| | | |
|---|---|---|
| PWARX model | – | PieceWise linear AutoRegressive model with eXogenous input |
| QUADRAE | – | QUAntitative DRiver behaviour modelling for active safety Assessment Expansion |
| QUADRIS | – | Improved QUAntitative DRIver behavior models and Safety assessment methods for ADAS and AD |
| ROPE | – | Region Of Practical Equivalence |
| SAE | – | Society of Automotive Engineers |
| SDG | – | Sustainable Development Goal(s) |
| SHRP2 | – | Strategic Highway Research Program 2 |
| SSARX model | – | Stochastic Switched AutoRegressive model with eXogenous input |
| SUT | – | System Under Test |
| TRB | – | Transportation Research Board |
| TTC | – | Time To Collision |
| ViP | – | Virtual Prototyping and Assessment by Simulation |
| VMT | – | Vehicle Miles Traveled |
| VTI | – | Statens Väg- och Transportforsknings Institut (Swedish National Road and Transport Research Institute) |
| VTTI | – | Virginia Tech Transportation Institute |

# Contents

# CHAPTER 1

# Introduction

Road injuries constitute the leading cause of death for children and adolescents aged 5–29 years (World Health Organization, 2018). In 2021, almost 20,000 people in Europe, and approximately 1.3 million people worldwide, were killed as a result of traffic accidents (in all age groups), and many more were severely injured (World Health Organization, 2019). Apart from the enormous distress and suffering caused to the victims and their families, road crashes bring about considerable economic loss for society. In most countries, the cost amounts to approximately 3 % of the gross domestic product (World Health Organization, 2018). Common crash-causation mechanisms include human factors, road conditions, vehicle failures, and light and weather conditions; human factors are the dominating cause. The literature reports human error to be the leading factor in approximately 90 % of all road traffic accidents (Castro, 2009; Dingus et al., 2016; Singh, 2018). Knowledge about drivers' behaviors, expectations, and performance limits is thus essential to mitigate human errors and, as a consequence, improve road safety.

Road crash and injury rates have declined with the increasing presence of advanced driving assistance systems (ADAS), such as lane-keeping systems (LKS) and advanced emergency braking (AEB) systems, which are becoming

standard in new cars. For example, on US roads, the number of fatalities went down from 1.46 per 100,000 vehicle miles traveled (VMT) in 2005 to 1.11 in 2019, despite an increase in the number of vehicles on the roads (National Center for Statistics and Analysis, 2022). Whereas a considerable part of this decrease may be attributed to updated safety regulations, increased seat belt usage, and better in-crash (passive) safety systems, the possible impact of ADASs should not be overlooked (the effectiveness of ADASs for crash frequency reduction is discussed in, e.g., Cicchino, 2017; Isaksson-Hellman & Lindman, 2018, 2019; Masello et al., 2022). Crash rates are expected to continue to decline due to updated legislation, such as the EU regulation that took effect in 2022 making LKS and AEB mandatory in new passenger cars and light commercial vehicles (European Union, 2019). Additionally, improving road safety, saving lives, and reducing suffering align with the United Nation's sustainable development goals (SDG; target 3.6 and 11.2; United Nations, 2015).

Understanding the driver-system interaction and how individual drivers can be expected to respond to upcoming threats is necessary to optimize the real-life efficiency of ADASs and evaluate to what extent the systems fulfill their purposes. Mathematical representations of driver behavior (computational driver models) enable virtual verification and validation of ADASs and automatic driving (AD) systems, thereby decreasing the need for real-world or test-track testing using physical vehicles and human drivers. Furthermore, driver models provide the possibility to adapt thresholds for ADAS warnings and for control interventions to the current driver in real time. Personalizing ADASs can enable earlier system interventions for unskilled or novice drivers without compromising more experienced drivers' system acceptance. Numerous models aiming to explain, identify, or mimic human driving control have emerged during the last 70 years, often targeting specific driving tasks or kinematic situations (e.g., car-following or lane-keeping; Markkula et al., 2012a).

An important application of driver behavior models is as ADAS-integrated models, to guide the shape of control interventions or adjust the timing of potential warnings to each individual driver (Lin et al., 2014; Panou, 2018; Yi et al., 2020). Individualized adaptation contribute to high system acceptance, since warnings that are appropriate on a population level can be perceived as disturbing by some (individual) drivers. Ill-timed warnings may also reduce

trust and create a reluctance to use the corresponding ADAS (Bliss & Acton, 2003; Cabrall et al., 2020; Coelingh et al., 2007). Attempts have been made to minimize false warnings and interventions by allowing system activation as soon as drivers exceed their comfort zone boundaries (CZB)—that is, when the driver is unable to resolve the situation *comfortably* (Bärgman, Smith, & Werneke, 2015; Ljung Aust & Engström, 2011; Sander, 2017; Summala, 2007; X. Yang et al., 2022). The CZB can be defined as an individual driver's maximum preferred steering and deceleration rates. A recent study demonstrated that an AEB system with activation thresholds based on a predefined CZB (estimated at a group level) has a much higher safety performance than a conventional AEB system (X. Yang et al., 2022). However, as pointed out by Bärgman, Smith, and Werneke (2015), there are considerable individual variations in CZBs, indicating that personalized ADASs with real-time adaptation capabilities would provide still better safety performance.

A few attempts have been made to construct driver models intended for ADAS integration and continuous (online) system adaptation. These models include intent recognition models which predict upcoming driving maneuvers (Jain et al., 2015; I.-H. Kim et al., 2017; Kuge et al., 2000; McCall & Trivedi, 2007; Oliver & Pentland, 2000; C. Wang et al., 2023), classification models for estimating driving style and driver state (Akita et al., 2007b; Augustynowicz, 2009; Fridman et al., 2017; Hsiao, 2008; G. Li et al., 2017; Quintero M. et al., 2012), and models for time series estimation of steering control or pedal operation (Angkititrakul et al., 2012; Hamada et al., 2016; Mikami et al., 2010; Taguchi et al., 2009). To this end, machine learning (ML) methods and other black-box models (based on, for example, artificial neural networks) are increasingly popular. However, these methods have obvious drawbacks, due to the computational power required and the challenge of understanding the non-intuitive nature of the model mechanisms. (However, the interpretability of ML-based models may improve with the recent advances in explainable artificial intelligence; see, e.g., Linardatos et al., 2021.)

Simpler probabilistic models are a feasible alternative to black-box models. Stochastic modeling based on hybrid dynamical systems (HDS; Akita et al., 2007a) constitutes a promising approach to real-time prediction and classification of driving behavior, due to the combination of discrete events and continuous dynamics in a single model. However, HDSs have previously been applied mainly to car-following (Akita et al., 2007a; Ikami et al., 2011; Okuda,

Ikami, et al., 2013); the necessary model complexity to achieve accurate predictions has not previously been studied.

This thesis demonstrates the applicability of a specific HDS family, hybrid autoregressive models with exogenous input (hybrid ARX models), to the lateral control domain by enabling real-time steering angle prediction and classification of driving style. This work also explores drivers' car-following behavior and whether there is an actual benefit to using complex predition models instead of simpler modeling alternatives.

Computational driver models intended for prospective virtual safety assessment (which estimates the safety potential of a future system) have the benefit of not requiring online model parameter estimation, thus enabling a higher level of model complexity. Nevertheless, there is a strong tradition of using simple threshold-based perception-reaction time models in this area (see, e.g., Green, 2000; Muttart, 2003, 2005). The driver behavior is then assumed to follow a deterministic, information-processing sequence comprising detection, cognitive processing, decision-making, and response execution (Engström et al., 2022; Markkula et al., 2012a). Several attempts have been made to quantify the perception-reaction time (Green, 2000; Olson, 1989), but the studies have been criticized for not considering situational urgency (Summala, 2000).

More recent publications have taken inspiration from ecological psychology acknowledging how the current kinematic situation influences response times (Engström, Bärgman, et al., 2018; Markkula, 2014, 2015; Markkula et al., 2016). Markkula (2014, 2015) outlines a conceptual driver model trying (in a simplified manner) to mimic the cognitive and neurological processes underlying drivers' decision-making. He suggests that drivers' braking behaviors can be described by noisy evidence accumulation of visual input (Boag et al., 2023; Gold & Shadlen, 2007; Purcell et al., 2010; Ratcliff, 1978; Usher & McClelland, 2001). In other words, brake initiation is modeled as a decision-making process acting on imperfect information (noisy evidence) collected over time. Markkula (2014) also proposes a conceptual driver modeling framework based on well-proven neuroscientific concepts, such as predictive processing (Clark, 2013, 2015), and the use of motor primitives (S. Giszter, 2009). A similar framework targeting generic driver modeling is suggested by Engström et al. (2022).

While conceptual driver modeling frameworks for virtual safety assessments exist, there is a lack of computational driver models that are mature enough

to be applied in simulations. This thesis meets this need by presenting a kinematics-dependent computational model of driver brake initiation and modulation, demonstrating how the model parameters can be estimated using real-world crash and near-crash data.

Models of human braking behavior have generally reached a higher maturity level than their counterparts in steering behavior. While multiple steering models have been proposed to describe curve-taking or lane-keeping behavior during routine driving, there is still no consensus on which perceptual quantities drivers use to guide lateral control. Common modeling paradigms are variations of the two-level steering model developed by Donges (1978). In this model, steering is guided at a compensatory level of control by near-vehicle information (e.g., lane position) and at an anticipatory level of control by information from further away (e.g., global optic flow). The control levels are often quantified using one or several aim points ahead of the vehicle (Benderius, 2014; Donges, 1978; Kondo & Ajimine, 1968; Salvucci & Gray, 2004; Zhou et al., 2020). However, more research is needed to understand the details of drivers' sensory-motor processes, particularly to facilitate the modeling of evasive steering.

Recently, alternative steering models based on perceptual input directly available to the driver have been proposed (Lappi & Mole, 2018; Martínez-García & Gordon, 2018; Martínez-García et al., 2016). Due to the brain's predisposition to detect and interpret angular information (Attneave, 1954; Hubel & Wiesel, 1968; Loffler, 2008; Yacoub et al., 2008), the perceptual input is often expressed in angles (Martínez-García & Gordon, 2018; Salvucci & Gray, 2004). Furthermore, Goodridge et al. (2022) demonstrate that steering initiation can be described as a response to perceptual error accumulation (i.e., the steering response times are better described by integrating the perceptual error over time than by using a constant threshold on the perceptual input). Similarly, Markkula et al. (2018) outline a lane-keeping model based on predictive processing and evidence accumulation. However, their model is intended for routine driving, which is not necessarily generalizable to critical situations. In fact, drivers' emergency maneuvers appear to be inherently different from routine driving (Adams, 1994; Koppa & Hayes, 1976; Markkula, 2015). Consequently, models of drivers' steering responses to upcoming threats, such as unintended lane departures, are still lacking. To close this knowledge gap, potential model structures and appropriate perceptual

quantities to guide steering control need investigation. This thesis takes an initial step towards modeling drivers' recovery maneuvers in unintended lane departures by exploring the potential of a set of lane departure risk metrics, quantifying the driver's subjectively perceived risk of an imminent lane departure for use as model input.

Last but not least, it must be mentioned that currently available computational models of driving control generally ignore visual distraction effects, assuming the driver is constantly attentive (Johns & Cole, 2015; Kolekar et al., 2017; Markkula et al., 2018; Salvucci & Gray, 2004). On the other hand, models exist which assume the driver to be completely blind to road conditions when directing the gaze away from the road (Bärgman, Lisovskaja, et al., 2015; Bärgman et al., 2022; Michaud, 2018; H. H. Yang & Peng, 2010). Neither of these assumptions is, of course, realistic. Although off-road glances are associated with delayed control responses, it is still possible for the driver to detect a threat and decide to brake or steer using peripheral vision (Lamble et al., 1999; Summala et al., 1996, 1998). Peripheral vision has been proven to play an essential role in driving (Higgins et al., 1998; Vater et al., 2022; Wolfe et al., 2019); as such, future driver models should naturally allow the simulated drivers to exhibit realistic human behavior patterns. This thesis demonstrates how the glance's visual eccentricity relative to the road ahead influences threat detection and control behavior in critical lead vehicle situations, and integrates part of this knowledge into a brake response model. This thesis also investigates the timing of corrective steering adjustments in unintended lane departure situations relative to the last off-road glance.

## 1.1 Aim and scope

This thesis aims to investigate how human driving behavior can be described through computational models—whether intended as an intrinsic part of ADAS algorithms or for application in the development, verification, and validation of ADASs. In particular, the thesis focuses on two main model application areas which together span the entirety of the ADAS development-verification chain: (1) online tuning of ADASs to the current driver (i.e., real-time system adaptation); and (2) virtual safety benefit assessments by counterfactual simulations with the driver in the loop (including, but not limited to, prospective evaluations of ADASs).

### General research questions

The main research questions addressed in this thesis are:

1. How can driver behavior be estimated in real time to enable online tuning of ADASs?

2. How can driver behavior in critical situations be computationally modeled?

3. How does gaze direction influence the driver's behavior in critical situations?

Papers 1–2 address the first research question; Papers 3, 4, and 6 concentrate on the second research question, and Papers 4–6 contribute to answering the third research question.

### Specific research questions

The general research questions were broken down into a subset of more specific questions targeted by the appended papers:

**RQ 1.1:** How can real-time driver identification suitable for tuning ADASs be achieved? (Papers 1–2)

**RQ 1.2:** What level of model complexity is necessary to predict car-following behavior in real time? (Paper 2)

**RQ 2.1:** How can the predictive processing and noisy evidence accumulation framework be leveraged to create a model of human braking behavior? (Papers 3–4)

**RQ 2.2:** Which risk metrics are suited to the application of modeling steering amplitude in lane departure recovery maneuvers? (Paper 6)

**RQ 3.1:** How can the performance of a human braking initiation and modulation model be improved by considering glance direction? (Paper 4)

**RQ 3.2:** How does the driver's gaze eccentricity impact glance and brake response times in critical lead vehicle scenarios? (Paper 5)

**RQ 3.3:** How is the initiation of the corrective steering maneuver related to the driver's gaze direction (on-/off-road) in unintended lane departures? (Paper 6)

## Thesis scope

In this thesis, driver behavior modeling is targeted in a relatively broad sense, with potential applications to both routine driving and critical situations. Models for both longitudinal (pedal operation) and lateral (steering) control are suggested. Figure 1.1 provides an overview of how each appended paper maps to the driving stages preceding a crash (i.e., routine driving or critical situation), the different control modalities (i.e., longitudinal or lateral), and whether driver glance behavior is considered or not. The longitudinal control models (Papers 2– 4) are restricted to pure (critical and non-critical) lead vehicle scenarios. In contrast, the lateral control models concentrate on curve-taking behaviors (Paper 1 and unintended lane departure situations (Paper 6). Two main frameworks were considered for the models: (1) hybrid ARX models (Papers 1–2); and (2) predictive processing with noisy evidence accumulation (Papers 3–4).

Both adopted frameworks in this thesis allow for relatively tractable and easily interpretable model structures. Due to the difficulty of analyzing models based on deep learning and neural networks, they are out of the scope of this work. Moreover, this thesis does not target driver models specifically intended for modeling crash-causation mechanisms (e.g., to generate baseline

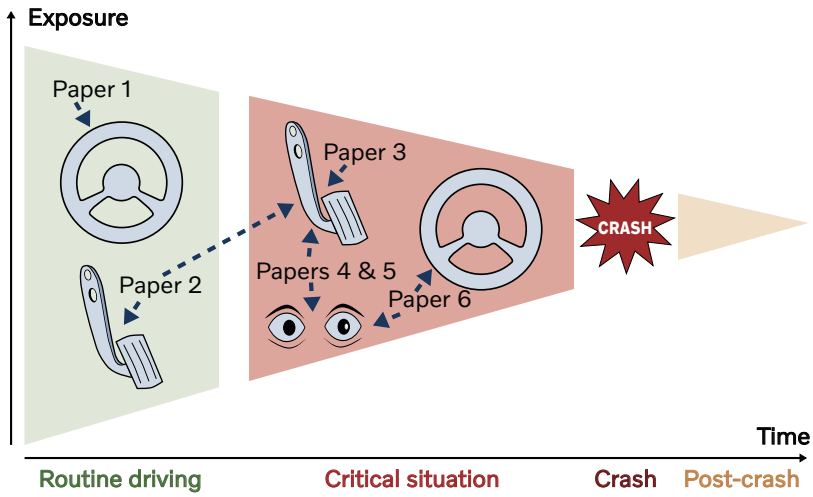


**Figure 1.1:** A schematic overview of each paper's focus areas. The steering wheels represent lateral control, and the pedals illustrate longitudinal control. The eyes reveals that driver gaze behavior has been taken into consideration.

cases in scenario-based safety assessment), road user interactions (taking into account the mutual interaction between the driver and other road users), or driver responses to infrastructure. Computational models intended for (multi-agent) traffic simulations are also beyond the scope of this thesis. As for the perceptual mechanisms considered, only visual information is expressly included in the models; vestibular input, for example, is not.

# CHAPTER 2

# Background

This chapter introduces computational driver behavior modeling for road safety applications. It also provides an overview of how visual attention, quantified by gaze direction, may influence driver behavior. Towards the end of the chapter, the use of computational driver models is put into context through the introduction of virtual-driver-in-the-loop simulations, focusing on one of the most common application areas related to traffic safety: virtual safety benefit assessment.

## 2.1 Computational driver behavior models

Computational driver behavior models are mathematical representations of human driving behavior, usually concentrating on motor responses to cognitive or neurobiological processes. These models have beneficial applications in various fields; one of the most common is vehicle safety. Within the field of vehicle safety, there are several sub-applications for which different kinds of driver models are appropriate. These include, but are not restricted to:

- Path tracking (Lazcano et al., 2021; Liu et al., 2022; Roy et al., 2009; Taheri et al., 2012)
- Anomaly detection—for example, distraction or sleepiness detection (Al-Gburi et al., 2023; Aljohani, 2023; J. H. Yang et al., 2009; M. Zhang et al., 2017)
- Crash causation (Bärgman et al., 2022; Fries et al., 2022; Imberg et al., 2022)
- Driver intent or maneuver recognition (Jain et al., 2015; I.-H. Kim et al., 2017; Kuge et al., 2000; McCall & Trivedi, 2007; Oliver & Pentland, 2000; C. Wang et al., 2023)
- Driving style classification (Akita et al., 2007b; Augustynowicz, 2009; Fridman et al., 2017; Hsiao, 2008; G. Li et al., 2017; Quintero M. et al., 2012)
- Behavior prediction (Angkititrakul et al., 2012; Hamada et al., 2016; Mikami et al., 2010; Taguchi et al., 2009)

Most early driver models were based on control theoretical concepts and focused on routine driving. They were mainly intended to control virtual drivers in traffic flow simulations (e.g., to describe car-following dynamics; Forbes, 1963; Gipps, 1981; McRuer & Weir, 1969; Newell, 1961; Pipes, 1953). While computer simulation is still a dominating application area for driver models, the focus has shifted towards virtual safety evaluation, where traffic flow is just one of the possible components.

The use of virtual testing to study the effect of a specific ADAS is a cost-efficient alternative, or a complement, to analyses of accident statistics (e.g., using insurance claims) or quantitative studies of real-world crash data (e.g., from in-vehicle event data recorders). Another clear advantage of simulation-based assessment is the possibility of evaluating potential effects of future or conceptual ADAS functionality, because the historic crashes needed to do a retrospective statistical assessment are not yet available. However, prerequisites for ecologically valid simulation results are sufficiently accurate representations of the driving environment, the vehicle dynamics, and, not the least, the driver behavior.

As more ADASs become standard in new vehicles, the need to model drivers' responses to warnings and system interventions increase. Likewise, there is a growing demand for models that mimic or assess routine driving behavior for integration into ADASs or AD systems. The increased interest in personalized

ADASs is motivated by their improved efficiency over conventional systems, which do not explicitly consider individual preferences (Lefèvre et al., 2015; J. Wang et al., 2016; X. Yang, 2023; X. Yang et al., 2022).

The structure of computational driver models, from simple linear models to complex ML models, must be adapted to the intended application (Abuali & Abou-Zeid, 2016; Markkula et al., 2012b). This thesis concentrates mainly on tractable driver models, which are easy to understand and analyze while representing driving behavior realistically.

Models used in real-life applications, such as continuous ADAS tuning, must be relatively generic (i.e., valid for various driving situations) and have structures enabling online parameter estimation. Consequently, clear restrictions on model complexity are imposed. However, such restrictions do not apply to models intended for offline use, since cognitive plausibility and the ability to replicate typical driver behavior in particular situations are most important. Thus, the same modeling paradigm may not be suitable for both online (real-time) and offline driver models—or the various sub-areas of application within these model categories. There is, however, no absolute partition of driver modeling methods, and much can be gained from taking inspiration from several areas.

This thesis addresses two main modeling paradigms: The first, for online use (e.g., ADAS tuning), comprises behavior prediction and classification models; the second, for offline applications (e.g., virtual safety benefit assessment), comprises cognitive driver models.

## Behavior prediction and classification models

Time series prediction and classification of the individual driver's current behavior enable real-time automatic tuning of ADASs. Thus, thresholds for warning and control interventions can be adapted to the current driver state or driver preferences, and settings related to comfort systems can be individually modified. Complex (black-box) models (e.g., reinforcement learning models, gaussian mixture models [GMMs] and hidden Markov models [HMMs]) dominate the behavior prediction and classification literature (Jain et al., 2015; Miyajima & Takeda, 2016; W. Wang, Xi, & Zhao, 2018; Zhao et al., 2022). However, white-box (with full transparency) or gray-box models (with some degree of interpretability) allow a more intuitive understanding. White-box models also facilitate model analyses and real-time parameter estimation.

Although black-box models are out of the scope of this thesis, it is warranted to study the HMM structure in more detail due to its similarities with the models applied in Papers 1–2. HMMs (see, e.g., Visser et al., 2009, for an introduction) are particularly attractive for time-series prediction applications, which predict a sequence of output values (e.g., the evolution of the steering angle signal over time) based on current and previous values. This kind of model describes the driving control sequence through the transition between discrete states (modes), each associated with an observed output (e.g., the steering angle may depend on the driver's internal mood) and specific probabilities of transitioning to the other discrete states in the model (e.g., as the mood changes). Being inherently probabilistic, HMMs may also be suitable to reflect the stochasticity in human behavior. However, the non-observability of the internal modes (i.e., the states are hidden) compromises model interpretability.

A more transparent alternative to HMMs, the hybrid dynamical system (HDS) paradigm, has emerged as a useful tool in the construction of driver models for behavior prediction and classification. Like HMMs, HDSs model driver control through a set of modes associated with, for example, specific maneuvers, driving styles, or comfort levels. However, in contrast to HMMs, all HDS modes are observable and thus provide information about the driving dynamics, which makes it easier to interpret the model. In brief, an HDS can be considered a discrete-event system with continuous dynamics to model the behavior corresponding to each discrete mode. As such, the models provide information on both the drivers' control behaviors and their decision-making processes (Akita et al., 2007a, 2007b; Nwadiuto et al., 2021).

Moreover, the variability in human driving behavior can, using HDSs, be reflected by online estimation of the mode-switching probabilities. For example, suppose a model has one mode describing alert and attentive driving and one describing sleepy and inattentive driving. A driver may start off the journey being alert (i.e., the model estimates a high probability of operation in the alert mode), but become more sleepy over time (i.e., the probability of being in the alert mode gradually decreases, and the sleepy mode probability increases). After stopping to rest, the driver may be identified as operating in the alert mode again, and consequently, the probability of shifting to the sleepy mode in the model decreases.

While pure driver behavior classification can be achieved using data mining

techniques such as clustering and principal component analysis (PCA; Constantinescu & Vladoiu, 2010; X. Song & Cao, 2022), the HDSs enable not only classification based on the current mode affiliation but also simultaneous time series prediction of driving control (e.g., steering angle or pedal operation). Behavior classification can be used, for example, to identify the current driving style as belonging to one of several potential categories—or to judge which kind of control strategy the driver is currently using (e.g., collision avoidance or car-following; Akita et al., 2007a, 2007b; Mikami et al., 2010; Nwadiuto et al., 2021).

There is a great flexibility in the choice of model to describe the dynamics of each mode in the HDS. Multiple publications describe autoregressive models with exogenous input (ARX-models) for this purpose, resulting in models referred to as hybrid ARX models in this thesis; see Section 3.2. Several hybrid ARX models have been applied to driver modeling. The model variants differ mainly in their mode-switching characteristics: the switching could be deterministic (e.g., piecewise ARX models, PWARX; Akita et al., 2007a, 2007b) or stochastic (e.g., stochastic switched ARX models, SSARX; Sekizawa et al., 2007). In recent years, autoregressive models have been combined with HMMs (i.e., approaching black-box modeling; Hamada et al., 2016).

The probabilistic ARX (PrARX) model is a stochastic hybrid ARX model which allows the driver to operate in multiple modes simultaneously. Moreover, its structure allows for a computationally easy parameter estimation process (Taguchi et al., 2009). The model output is calculated by weighting the outputs of the ARX models of all modes, with weights corresponding to the probabilities of the system being in each mode. Taguchi et al. (2009) and Okuda, Tazaki, and Suzuki (2013) demonstrated the application of a PrARX-model to describe longitudinal driving behavior for vehicle-following, and Mikami et al. (2010) attempted to combine a similar model with a model predictive control (MPC) algorithm integrated into a brake assist system. Their algorithm was designed to minimize the time spent in modes where the driver exhibited collision avoidance behavior. However, since the parameters were only estimated offline, the model did not adapt to behavior variations during driving (resulting from, for example, shifts in driver state or in the driving environment).

Moreover, the concept of “decision entropy” for hybrid ARX models was introduced by Taguchi et al. (2007). It quantifies the level of hesitance in the

mode switching process by measuring how much time the model spends simultaneously in multiple modes (which corresponds to the transition phases between single modes). Low decision entropy results from instant mode switches (i.e., the model operation is dominated by a single mode at a time). In contrast, hesitant mode-switching behavior yields high entropy values (i.e., a lot of time is spent transitioning between modes). Decision-entropy has been used in PrARX models to estimate the driver's current distraction level (K. Kato et al., 2013).

The potential benefits and applications of hybrid ARX models are further investigated in Papers 1–2 of this thesis. Specifically, PrARX models are used to predict and classify both longitudinal and lateral driving behavior.

## Cognitive models

Cognitive models aim to represent the sensory processing and decision-making processes in the human brain. In a car driving context, these representations may yield a deeper understanding of the mechanisms influencing driving and contribute to the creation of model outputs with high ecological validity. In addition, psychologically plausible driver models may enable generalizations to previously unseen kinematical situations.

Visual perception is the main information source which guides driving (Hills, 1980). Furthermore, reproducing other sensory modalities in the simulation environments where the driver models will be applied may be challenging. Therefore, most cognitive driver models are based on visually available input, such as the perceived size change of an approaching lead vehicle (Engström et al., 2022; Engström, Markkula, et al., 2018; R. Kiefer et al., 2003; Kondoh et al., 2014; Markkula, 2014).

Constructing cognitive models requires in-depth knowledge of driver behaviors and how biological (neurological) processes influence these. As a result, the models risk becoming very complex. On the other hand, the models are easy to analyze and have high levels of generalizability. Possible application areas include: describing the negotiation of highly critical situations, acting as autonomous agents in microscopic traffic simulations (simulating routine driving), and planning suitable trajectories for AD system maneuvers. Depending on the exact model structure, it could also be possible to use cognitive models for behavior prediction or classification; this possibility is discussed in more detail later in the thesis (see Section 5.4). Defining the exact stimulus that

drivers react to, and the nature of the reaction, is, however, often challenging (see, e.g., Fajen & Devaney, 2006).

An increasingly popular cognitive driver modeling approach is (noisy) evidence accumulation of perceptual input. Analogous to the neurological processes of neuron action potential firing triggered by a certain (noisy) stimulus (Purcell et al., 2010; Usher & McClelland, 2001), the accumulation paradigm assumes that evidence for a specific action (or decision) is accumulated over time (Gold & Shadlen, 2007; Usher & McClelland, 2001). Evidence accumulation models, traditionally used to model human decision-making processes, have been applied in experiments in which the respondents were asked to choose between two responses depending on a visual stimulus (e.g., whether a colored light is red or green; Usher & McClelland, 2001). Furthermore, it has been used to model decision-making and response times in various application areas—for example, by Neal and Kwantes (2009) for conflict detection in air traffic control; by Sabanovic and Matuzevicius (2015) for image analysis; and by Durso et al. (2015) for strategic threat-management in pediatric intensive care. In the automotive domain, Ratcliff and colleagues (Ratcliff, 2015; Ratcliff & Strayer, 2014) used a drift-diffusion model (Ratcliff & Van Dongen, 2011), which is a subtype of accumulation model acting on a single continuous variable, to model driver response times to brake light onset. In addition, Markkula (2015) was the first to suggest that a comprehensive conceptual framework based on noisy evidence accumulation, in combination with a prediction of sensory inputs, is a suitable approach for modeling human driving behavior. Markkula's work also assumed incremental vehicle control using basic kinematic motor primitives (S. Giszter, 2009; S. F. Giszter, 2015), such as braking in discrete steps (Markkula, 2014), or steering using intermittent ballistic steering adjustments (Benderius & Markkula, 2014; S. Giszter, 2009; S. F. Giszter, 2015; Markkula et al., 2018; Martínez-García & Gordon, 2018).

With the assumption that drivers act upon the perceived difference between expected and actual sensory stimuli rather than the actual input per se, Markkula's framework fits well with the *predictive processing* theory (Clark, 2013, 2015). The predictive processing paradigm is derived from Friston's free energy principle (Friston, 2009, 2010), which assumes that any self-organized system (such as the brain; Singer, 2009) must minimize the difference between their internal representation of the world and the perceived sensory informa-

tion, the *free energy*, to maintain equilibrium. The paradigm is a formal mathematical framework which considers the mind to be a predictive dynamical system (similar to the "Bayesian brain" introduced by Doya et al., 2011). All motor actions are assumed to strive to suppress perceptual prediction errors (where the predictions may be updated over time) through a combined perception-action process called *active inference* (Friston et al., 2017; Parr et al., 2022). To minimize prediction errors (which under simplified conditions are equivalent to free energy; Friston, 2009), the brain can update its current beliefs to match what is perceived (e.g.,when approaching a car ahead, the belief changes from "I am driving at a constant time headway" to "My time headway is decreasing"). Alternatively, the brain can elicit a motor action to generate perceptual input which is consistent with the beliefs (e.g., brake in order to reattain the constant time headway when approaching the car ahead; Clark, 2013; Friston et al., 2017). A thorough attempt to conceptually employ predictive processing and Friston's principles to understand human factors in automobile driving was presented by Engström, Bärgman, et al. (2018). The authors showed that mismatched driver expectations (predictions) may lead to critical situations. The discussion was subsequently advanced by Engström et al. (2022), who propose a novel modeling framework based on active inference and the information-theory concept of surprise (defined as the negative logarithm of an outcome probability, which is similar to prediction error; Friston, 2009, 2010; Itti & Baldi, 2009). Engström et al. (2022) demonstrate the properties of the framework in an example of a simple brake initiation model incorporating an ML-based generative model to estimate driver expectations. Active inference has also been used to model emergency responses to automation failure (Wei et al., 2022). Furthermore, Wei et al. (2023) showed that an active inference-based car-following model, the Active Inference Driving Agent (AIDA), had an accuracy comparable with neural network-based models, while providing superior interpretability and cognitive plausibility.

In this thesis, the predictive processing framework and noisy evidence accumulation are further explored (although not on the free energy or active inference level) and applied to modeling drivers' evasive brake responses to critical lead vehicle situations (Papers 3–4).

## 2.2 Vision and attention in driving

Attention may refer to a wide range of human states—for example, arousal (Raskin, 1973), consciousness (Posner, 1994), or effort (Kahneman, 1973). Here, it is defined in contrast to its opposite: inattention, which somehow impairs the driver's situation awareness or alertness level. Some examples that result in inattention include sleepiness, cognitive distraction, and inappropriate off-road glances. While attention may be governed by many different cognitive processes and sensory modalities, this thesis' main focus is on *visual* attention, quantified by the driver's gaze direction. Visual attention can be considered a selection mechanism that filters the enormous amount of information entering the visual field and finds what is relevant to the task at hand (see, e.g., Lamme, 2005). Thus, drivers must constantly scan the environment and use their attention to identify what information to act upon. Since the visual field is limited in both acuity and field of view, drivers must divert their gaze (and sometimes also move their head and torso) from the road ahead to, for example, the side mirrors or the speedometer. Safe driving relies on these necessary off-road glances (Kircher et al., 2020).

While some off-road glances are inherent to safe driving, many arise from the driver's desire to perform tasks secondary to driving. With the ever-increasing number of mobile devices and in-vehicle systems, drivers are continuously tempted to divert their attention from the road ahead (e.g., by tuning the radio or texting on the phone). Unfortunately, the secondary tasks compete with the principal driving task for visual and attentional resources, and may thus deteriorate driving performance (Engström, 2011). In fact, US studies show that distraction has a prominent role in more than 20 % of all crashes, with fatalities both inside and outside the vehicle (S. Klauer et al., 2006; Yue et al., 2020). In addition, even though drivers often wait until low-complexity driving situations to initiate secondary tasks (Tivesten & Dozza, 2014), studies associate long glances away from the road with an increased crash risk (Horrey & Wickens, 2007; S. G. Klauer et al., 2014; T. Victor et al., 2014).

It is essential to understand the attention allocation processes and the factors influencing attention duration to understand and model the drivers' actions (and thus potential mistakes). Although cortical areas controlling eye movements overlap with those controlling attention (Corbetta, 1998), what drivers see is not always the same as what they attend to (Salvucci, 2000). The driver may be looking at something without paying attention due to cog-

nitive distraction (e.g., caused by a conversation with passengers) or looking away from something while still (at least partly) attending to it with their peripheral vision. In fact, cognitively distracted drivers tend to keep their gaze more concentrated on the forward roadway than attentive drivers, a counter-intuitive finding often referred to as the *gaze concentration* effect (Nilsson, 2022; Recarte & Nunes, 2003; T. Victor, 2005; Y. Wang et al., 2014). On the other hand, it is well established that drivers are able to perform certain tasks, such as lane keeping and threat detection, using peripheral visual information exclusively (Huestegge & Böckler, 2016; N. G. Kim, 2013; Lamble et al., 1999; Lehtonen et al., 2018; Summala et al., 1996). These aspects of driver attention, rarely included in computational driver models, could potentially improve model performance. A better understanding of how to model drivers' (visual) attention and its relation to peripheral vision would eventually contribute to preventing (or at least reducing) crashes caused by visual distraction, by integrating the knowledge into models used for the development and verification of ADASs.

## 2.3 Virtual safety benefit estimation and prospective safety assessment

Safety benefit estimation aims to investigate and quantify the effects that a specific ADAS, or other safety measure, has on the overall road safety. The assessment can be retrospective, analyzing the effect of already available, well-established ADASs. Retrospective assessments generally rely on statistical methods and data provided by insurance companies (Cicchino, 2017; Fildes et al., 2015; Isaksson-Hellman & Lindman, 2018, 2019; Zangmeister et al., 2016). Correctly performed, these assessments can provide estimates very close to the truth (Sander, 2018). Alternatively, the assessment can be prospective, estimating the potential future benefit of a not yet realized system (Alvarez et al., 2017; Gschwendtner et al., 2014; International Organization for Standardization, 2019; Jeppsson et al., 2018; Kovaceva et al., 2020; Sander, 2018). However, this type of evaluation cannot, in general, be performed with the above-mentioned retrospective assessment methods, because there is insufficient real-world crash data from vehicles equipped with the system under test (SUT) in addition to the crash data from vehicles without the SUT.

In recent years, computer simulation has emerged as a cost-efficient and

flexible approach to prospective safety assessments. It has a decent history in the development and verification of passive safety systems (such as airbags or mechanical structures targeting injury prevention; see, e.g., Wågström et al., 2019). Virtual evaluations require accurate mathematical representations of all relevant components: in the passive safety domain the required components are mainly finite element models of the vehicle, driver, and possibly occupants. In contrast, the pre-crash (ADAS) domain requires realistic, dynamic models of the driver, vehicle, and environment. Accurate driver models, used to create a baseline for safety evaluations, play an essential role in the generation of crashes (Bärgman et al., 2022; Fries et al., 2022; Imberg et al., 2022). These models also provide the possibility to study driver responses to different kinematic situations, as well as to ADAS warnings and interventions (Bärgman, Boda, & Dozza, 2017; Bärgman, Lisovskaja, et al., 2015; Haus et al., 2019; Rosén, 2013; Seacrist et al., 2020; X. Yang et al., 2022). In the future, advanced simulation environments may also make it possible to predict the effects of changes in infrastructure, policy, and even the proportion of automated driving systems in a mixed traffic environment. Certainly, accurate predictions require a reliable assessment of exposure to safety-relevant situations (e.g., number of registered vehicles or vehicle mileage; Dozza, 2017; Hauer, 1995; Sander, 2018), which remains a main methodological issue. Recent initiatives have been undertaken to standardize virtual safety assessment methods (Alvarez et al., 2017; International Organization for Standardization, 2021; Page et al., 2015; V4SAFETY, n.d.) in order to create a common, comprehensive assessment framework which would facilitate comparison of simulation outcomes from tests performed at different places and by different persons.

There are several ways to perform virtual benefit assessments: Scenario-based simulations concentrate on groups of specific kinematic situations that may be encountered in traffic, such as lead vehicle collisions (Riedmaier et al., 2020). Each scenario-based simulation is typically short (from a few seconds up to half a minute); the SUT is exposed to a specific critical situation, possibly with a virtual driver in the loop. An other possibility is to run multi-agent traffic simulations, mimicking a complex traffic system with multiple road users. Multi-agent traffic simulations can be used to analyze traffic at various levels: single vehicles (microscopic simulation), groups of vehicles (mesoscopic simulation), and general traffic flow (macroscopic simulation) (Ferrara et al.,

2018). Microscopic simulations are commonly used for safety assessments, since these focus on the behaviors of a specific (subject) vehicle rather than high-level road user interactions. However, validation of multi-agent simulation as a safety evaluation tool is much needed, particularly since it may be difficult to estimate how well the simulated kinematics and incidence rates of the generated crashes represent what can be observed on real roads.

Commercial simulation tools, such as IPG CarMaker (IPG Automotive, n.d.) or Simcenter Prescan (Siemens, n.d.), are readily available for performing virtual tests in a realistic environment. They include advanced vehicle dynamics models and, in some cases, even simple driver models. The driver models are mainly trajectory-following models, which can be tweaked to generate various driving styles (e.g., careful or aggressive driving). However, the flexibility to include one's own technological solutions, such as conceptual ADASs, varies between tools. An alternative to commercial tools is to use open-source software, such as Environment Simulator Minimalistic ("Esmini", n.d.) and OpenPASS ("OpenPASS Working Group", n.d.), to set up scenario-based evaluations. Some manufacturers have even chosen to implement simulation platforms tailored to their own vehicles, to have control over all parts of the simulation chain and achieve maximum flexibility (Hallerbach et al., 2018; Q. Song et al., 2021).

## Counterfactual simulation

Counterfactual simulation is a valuable tool in scenario-based virtual assessments (Bärgman, Boda, & Dozza, 2017; Bärgman, Lisovskaja, et al., 2015; Davis et al., 2011; Haus et al., 2019; Leledakis, Lindman, et al., 2021; McLaughlin et al., 2008; Rosén, 2013; Scanlon et al., 2021; Seacrist et al., 2020; X. Yang et al., 2022). In essence, the safety performances in specific pre-crash configurations (i.e., kinematics a few seconds before a critical event) are compared between vehicles with and without a particular safety measure (known as treatment and baseline conditions, respectively). The main aim of counterfactual simulations is to answer the question, "'What if?" (Bärgman, Lisovskaja, et al., 2015) as in, What if the following vehicle in a lead vehicle scenario had an AEB system which intervened? What if the vehicle did not? The performance metrics usually include the proportion of crashes in a specific (possibly synthetically generated) data set, but are sometimes more detailed and include information about change in impact speeds or injury risk (X. Yang, 2023).

The original pre-crash configurations, comprising the baseline data, may be based on synthetically generated scenarios from statistical observations of relevant crash mechanisms. These scenarios might include a crash causation driver model (Bärgman et al., 2022; Fries et al., 2022; Imberg et al., 2022), or reflect the kinematics from an actual critical situation (Rosén, 2013; Sander & Lubbe, 2018). In the latter case, the crash data used are often either recorded (e.g., from a naturalistic driving study such as Strategic Highway Research Program 2 [SHRP2]) or reconstructed (e.g., from a crash database such as the German In-Depth Accident Study; Schubert et al., 2012). A simple driver response model might be included to describe the evasive action (if any) and some variations of the parameters in each reconstructed situation—to account for uncertainties and generate a more extensive set of baseline kinematics (Alvarez et al., 2017). Data from near-crashes and routine driving events (e.g., lead vehicle braking events) may also be applicable. However, care should be taken when using non-crash data in simulations since the scenario kinematics may be substatially different from what is typically observed in crashes (Olleja et al., 2022).

### Virtual-driver-in-the-loop simulations

Two main types of driver models can be used in counterfactual simulations: one for scenario generation (typically, a model that can reproduce trajectories and crash kinematics) and one for the driver response, to be applied in the generated scenarios (Alvarez et al., 2017; Bärgman, Boda, & Dozza, 2017). Scenario-generating models are, however, not necessary when using individual and unmodified cases of recorded crash data.

The purpose of the driver response model is to describe the (potential) perceptual-motor actions effectuated by the driver, in response to the perceived urgency of a situation or to warnings and interventions issued by an ADAS (Bärgman, Boda, & Dozza, 2017; Seyedi et al., 2021; Sugimoto & Sauer, 2005, see also Paper 3). It is possible to perform simulations without a driver response model in the loop, but the realism of the output may be compromised (e.g., it would not make sense to evaluate a warning system without including a driver's reaction to it). Traditionally, simple statistical driver models based on perception-reaction time distributions and predefined evasive maneuvers have been used (Green, 2000; Muttart, 2003, 2005). However, recent research has demonstrated that the choice of driver model is essential and

can affect the results even when all other variables are unchanged (Bärgman, Boda, & Dozza, 2017). Thus, caution should be used in the model selection. Unfortunately, the choice of validated driver models is still very limited.

### Multi-agent microscopic traffic simulations

In contrast to scenario-based simulations, virtual-driver-in-the-loop simulations are sometimes performed using the more complex multi-agent microscopic traffic simulation platforms. Driver models intended for critical situations can be used in this kind of simulation environment as well, if complemented with models of routine driving behavior (e.g., the widely used Intelligent Driver Model introduced by Treiber et al., 2000). Microscopic traffic simulation is not dependent on previously collected data since it can independently generate critical scenarios using driver error induction methods or crash causation algorithms (Hallerbach et al., 2018; H. H. Yang & Peng, 2010). Two challenges with this approach are to ensure the representativeness of the generated crashes (by comparing them to field statistics) and to estimate exposure. Nonetheless, traffic simulation has the advantage of supporting the creation and simulation of entirely new kinds of crashes—which may, for example, arise in the future as vehicles with high levels of automation not yet on public roads achieve high penetration (Hallerbach et al., 2018; Jeong et al., 2017). In the same way, however, the approach may create completely unrealistic crashes (either in terms of exposure or crash characteristics) that do not represent real-world crashes.

# CHAPTER 3

# Method

This chapter presents the methods and tools that constitute the basis of the driver behavior modeling work in this thesis. Accurate models require representative data of sufficient quality, and the first section provides an overview of the different data collection options that have been explored. Subsequently, high-level descriptions of the main modeling frameworks and parameter estimation methods are provided. A brief look at the practicalities when applying driver models in a virtual simulation environment concludes the chapter.

## 3.1 Data collection

Since no model is better than the data on which it is based, it is imperative to use data which are as representative and non-biased as possible. The papers appended to this thesis use a wide range of data sets collected from different sources, all with their own benefits and drawbacks. All applied data collection methods and their implications for driver modeling are discussed below. First, descriptions of general data collection methods for driver-vehicle interaction and their respective driving environments are provided. Then, currently available methods for collecting glance data are addressed.

## Driver-vehicle interaction

Detailed and unbiased recordings of driver behavior are scarce, particularly of behaviors associated with critical situations. Real-world crash and near-crash data, available through extensive databases, must thus often be complemented with data from controlled experiments (e.g., driving simulator or test-track studies). Targeted evaluations of a specific ADAS, for example, may be performed using field operational tests (FOT). Critical situations are rare in such tests, but the data may be used to gain insight into routine driving behaviors.

In recent years, large amounts of naturalistic driving data (NDD) have been recorded, annotated, and stored in massive databases through projects such as the "European naturalistic driving and riding for infrastructure and vehicle safety and environment database" (UDrive; Bärgman, van Nes, et al., 2017), SHRP2 (National Academies of Sciences, Engineering, and Medicine, n.d.), and the 100-car naturalistic driving study (Dingus et al., 2006). In these studies, hundreds of privately owned cars were equipped with logging equipment, including cameras, and all trips were recorded during an extended period (more than a year). The drivers did not receive any specific driving instructions, and their behaviors were thus presumably representative of their ordinary driving. This kind of large-scale data collection is, of course, very costly and requires a lot of storage capacity and annotation work (e.g., manual coding of event characteristics or driver behavior; Hankey et al., 2016; Jansen et al., 2021). However, with data collection efforts of that magnitude, the probability of recording at least some safety-relevant events, including severe crashes, is high. Papers 3–4 used lead vehicle crash and near-crash data collected in SHRP2 to parameterize and validate driver models of evasive braking. Additionally, Paper 6 considered, in part, a few of the critical lane departure events captured in the SHRP2 study.

As with NDD, FOT data are collected from real vehicles driving on real roads. However, unlike most NDD, the aim is usually to test the performance of a specific safety measure. Evaluations of driver-state-focused ADASs, such as sleepiness and distraction warning systems or comfort systems (like ACC), are appropriate for FOTs. However, true positive tests of ADASs targeting highly critical situations are not (since these situations are rare). The general FOT setup includes both baseline driving, with no ADAS active, and driving with an activated ADAS (the SUT). Depending on the intended model application, both data sets can be used for driver modeling. Paper 6 partly based

the analysis of lane departure events extracted from baseline data collected in the Eyes On Road FOT, which contains data collected in ten cars driven by Volvo cars employees around the Gothenburg area (Karlsson et al., 2016). This relatively small data set did not include any severely critical events.

Apart from being scarce, the crashes in NDD (or FOT) represent a wide range of kinematics and environments, complicating the subsequent analyses. Therefore, controlled experiments may be an appealing option for studying specific aspects of driving behavior. Controlled tests are affordable (compared to NDD and FOTs), flexible, and offer a high level of repeatability. The realism, however, is compromised. Drivers' behaviors may be altered by the standardized or artificial driving environment and by the expectancy that something out of the ordinary may occur. Driver expectancy also makes repeated exposures to critical events problematic, requiring the recruitment of a high number of test participants (Eriksson et al., 2018; J. D. Lee et al., 2002; Ljung Aust et al., 2013). Moreover, each test participant must be given the opportunity to get confident with the vehicle and the driving environment and drive for a while before the critical event occurs, thus increasing the time required to conduct the study.

The two most common environments for controlled tests are driving simulators and test tracks. Experiments may also be performed in real traffic, though without the benefits of exact repeatability or the possibility of inducing critical events. High-fidelity driving simulators were used in Papers 2, 5, and 6 of this thesis. The two latter papers included critical event exposures (in Paper 5, a longitudinal lead vehicle event; in Paper 6, a lane departure event). Using state-of-the-art driving simulators ensured a realistic rendering of important visual quantities (such as the position and size of surrounding vehicles) and valid vehicle dynamics. Both these features are essential since inaccurate visual or haptic cues may impact the authenticity of drivers' control behaviors. In particular, differences have been observed in drivers' brake modulation between driving simulator data and data collected in corresponding situations on a test track or real roads (Boda et al., 2018; Hoffman et al., 2002).

In contrast to driving simulator experiments, test track studies have the advantage of being performed in real vehicles, in which visual and haptic cues are identical (or at least very close) to those experienced in a real-world situation. Unfortunately, test track studies offer less flexibility than driving simulator studies in terms of what is possible or suitable (e.g., safe). For

example, critical lane departures may be very difficult to induce safely. Driver reactions may also be affected by the use of balloon cars or inflatable dolls, which do not necessarily represent other road users very realistically (Chrysler et al., 2015). An increased level of realism may be achieved by combining real-vehicle driving with virtual or augmented reality, although this is still uncommon (Hartmann et al., 2017; Uchida et al., 2017). In this thesis, a small test track study was performed to demonstrate the potential of the driver model presented in Paper 1.

## Driver glance behavior

Knowing where the drivers allocate their visual attention is essential to determine and analyze the reason for specific driving behaviors. Gaze direction has been used as a surrogate for visual attention in most of the work in this thesis. However, as discussed in Papers 4–6, the use of peripheral vision allows for partial visual processing during off-road glances. Since peripheral vision enables quick gist perception (a rapid, overall impression of a scene or situation) and is used to plan shifts in attention and gaze, it is essential to information acquisition in driving (Wolfe et al., 2022).

Visual time-sharing between the road in front, other areas of interest (AOIs) relevant to the driving task (e.g., side and rear-view mirrors)—and sometimes AOIs secondary to the driving task (e.g., the center stack)—is integral to all driving. The gaze direction at a given time can be automatically estimated with eye-tracking equipment (e.g., using glasses or a system of driver-facing cameras) or by manually examining video recordings. A drawback of eye tracking (however determined) is that only the foveal gaze direction is considered. Thus, information about what the driver perceives in the extra-foveal and peripheral view is not available.

Moreover, the importance of context in gaze analysis should be emphasized (Ahlström et al., 2021). Contrary to what is often assumed, off-road glances are not necessarily detrimental to safety or an indication of driver distraction but may, in fact, be required for safe driving (Ahlström et al., 2021; Kircher et al., 2020). For example, when preparing for an overtaking maneuver, the driver needs to look in the side and rear-view mirrors and check for cars in the adjacent lane: in this situation, an on-road glance is not necessarily safer than an off-road glance. For this reason, Ahlström et al. (2021) propose to use a purposed-based approach to evaluate driver attention, assessing the

driver's gaze pattern (in terms of timing and duration) in relation to visual sampling areas relevant to the current driving situation.

For offline applications (e.g., posterior glance analysis), manual frame-by-frame annotation of video recordings from one or more driver-facing cameras—where the driver's eyes are clearly visible—is often employed (Jansen et al., 2021). However, Jansen et al. (2021) question the accuracy of this method, noting it depends on the number of annotation regions (AOIs) and the purpose of the gaze direction analysis. Manual annotation is, moreover, a time-consuming, tedious process, and several annotators should cover the same sequence to minimize the effects of subjective judgment. Methods to automate the annotation process exist (Fridman et al., 2016; Tawari & Trivedi, 2014; Vora et al., 2017) but suffer from a lack of reliable ground-truth data on which the algorithms can be trained (Jansen et al., 2021). Overall, frame-by-frame annotation based on video recordings is not suitable for long driving sequences. Instead, it may be a feasible alternative for studies of, for example, drivers' interactions with a (time-limited) secondary task or drivers' responses to induced critical events in a controlled study.

The use of automatic eye trackers may be attractive since they minimize the amount of manual work required to annotate even short driving sequences. However, the accuracy of the eye-tracker estimations can vary considerably between drivers, and the equipment is commonly vulnerable to incorrect calibration (Feit et al., 2017; Khan & Lee, 2019). Another major drawback is the system's limited reliability in naturalistic driving settings, due to, for example, shifting illumination conditions and vehicle vibrations (Holmqvist et al., 2012; Jansen et al., 2021; Khan & Lee, 2019). If data quality can be ensured, automatic eye trackers may be useful for real-time monitoring of the driver's gaze behavior, providing ADASs with information about the driver's current level of visual distraction or sleepiness (Fridman et al., 2017; Halin et al., 2021; Hayley et al., 2021; Ma et al., 2019). In fact, sleepiness and distraction systems (although not necessarily camera-based) are already mandatory within the EU (European Union, 2019). Further, the European New Car Assessment Programme, Euro NCAP (2022), encourages driver monitoring systems (DMS) in all new vehicles, with points awarded to vehicles in which the DMS can successfully detect distracted, sleepy, or unresponsive drivers.

Most glance data used in this thesis (Papers 3–6) were manually coded by at least two independent annotators. However, automatic eye tracking

by a system of multiple driver-facing cameras was used in the run-off-road simulator study presented in Paper 6.

## 3.2 Modeling frameworks

The intended application area is one of the main considerations in the modeling framework selection. Two appropriate frameworks were applied in this thesis: (1) the hybrid ARX framework, which is suitable for online parameter estimation, and (2) the predictive processing framework with noisy evidence accumulation, which is appropriate for offline applications (e.g., ADAS evaluation). Additionally, Bayesian regression models were used to explore risk metrics suitable for modeling driver behavior in critical lateral situations (lane departures). The regression models constitute a first step toward more complex models based, for example, on the predictive processing framework.

### Hybrid ARX models

Papers 1–2 use hybrid ARX models to model and classify driving behavior in both the lateral (Paper 1) and longitudinal (Paper 2) domains. The main modeling structure is a PrARX model, as described by Taguchi et al. (2009). PrARX models cluster driving behavior into discrete modes $S_i$ ($i = 1, \ldots, s$, with $s$ being the number of modes), and the behavior corresponding to each mode is described by ARX models. The ARX model output $y_t$ at time $t$ can be calculated as:

$$y_t = a_1 y_{t-1} + a_2 y_{t-2} + \cdots + a_n y_{t-n} + b_0 u_t + b_1 u_{t-1} + \cdots + b_m u_{t-m} + e_t, \quad (3.1)$$

where $e_t$ is an error term, and $a_1, a_2, \ldots, a_n$ and $b_0, b_1, \ldots, b_m$ are the model parameters; $n$ and $m$ are the orders of the ARX model. Assuming a parameter vector $\theta = [a_1, a_2, \ldots, a_n, b_0, b_1, \ldots, b_m]^T$ and a regression vector $\phi_t = [y_{t-1}, y_{t-2}, \ldots, y_{t-n}, u_t, u_{t-1}, \ldots, u_{t-m}]^T$, the ARX model can be written in compact form as:

$$y_t = \theta^T \phi_t + e_t. \quad (3.2)$$

The probability that the driver operates according to the ARX model in mode $S_i$ is expressed by a softmax function with switching parameters $\eta_i$:

$$P_i(\phi_t) = \frac{e^{n_i^T \phi_t}}{\sum_{j=1}^{s} e^{n_i^T \phi_t}}, \quad (3.3)$$

where a higher value of $n_i$ corresponds to mode $i$ having more impact on the total model output. This softmax formulation makes the PrARX model convenient for online parameter estimation, since both the sub-model (ARX) parameters $\theta_i$ and the switching parameters $\eta_i$ can be simultaneously estimated. The total PrARX model output will be the weighted sum of the behavior in all modes:

$$y_t = \sum_{i=1}^{s} P_i(\phi_t)\theta_i^T \phi_t + e_{i,t}. \tag{3.4}$$

A schematic representation of the PrARX model structure can be found in Figure 3.1.

PrARX models can be used for driver behavior classification by assuming that driver behavior in each instant belongs to the operating mode with the highest probability $P_i(\phi_t)$. Each mode corresponds to a certain driving style or behavior. In Paper 1, online parameter estimation of PrARX models is used to classify the driving behavior as either aggressive (mode 1) or non-aggressive (mode 2). In contrast, Paper 2 uses discrete model modes to judge whether drivers are within their comfort zone (mode 1), which is associated with a sense of being in complete control of the situation, or not (mode 2).

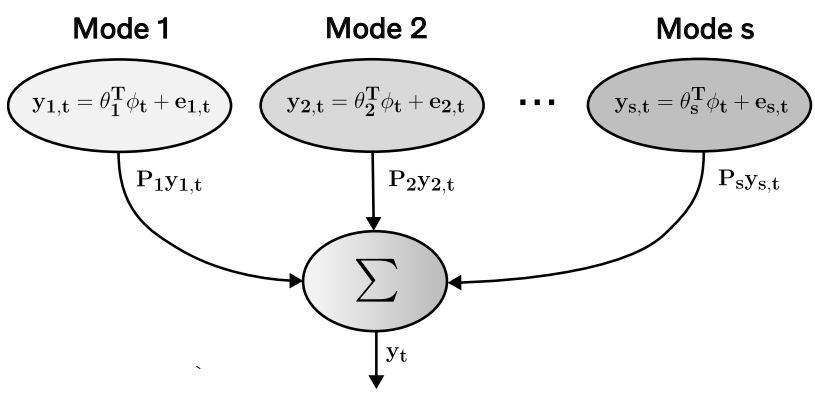


**Figure 3.1:** A schematic representation of the PrARX model structure.

## Predictive processing and noisy evidence accumulation

Offline driver model applications, such as virtual safety benefit assessments, allow higher flexibility in the model structures, since fast and efficient parameter estimation methods are secondary to model accuracy. Here, evidence accumulation (Boag et al., 2023; Gold & Shadlen, 2007; Usher & McClelland, 2001), a concept originating from cognitive science, has been combined with the predictive processing concept from neuroscience to describe driving control using kinematic motor primitives (S. Giszter, 2009; S. F. Giszter, 2015), which are guided by the prediction of sensory outcomes (Crapse & Sommer, 2008). In particular, the work in Papers 3–4 is based on the computational framework for driver modeling suggested by Markkula (2014) and Markkula et al. (2018), revolving around four basic principles:

1. Noisy evidence accumulation
2. Generation of motor primitives as intermittent control actions
3. Prediction of future perceptual inputs
4. Control adjustment magnitude tuned to the perceptual prediction error

While these principles are generic and can be applied to many different traffic situations, the work in this thesis focuses on kinematics-dependent models for braking in critical lead vehicle situations. Such situations are defined by the presence of a slower or stationary vehicle in front of the subject vehicle, causing the driver to brake (or steer) to avoid a collision; see Figure 3.2 for an illustration. The perceptual quantity used in these models is looming, which is (at least for small angles) a visually perceivable equivalent to time to collision (TTC). The looming describes the angular growth of the image of the lead car projected onto the observer's retina (D. N. Lee, 1976). Following the definition by D. N. Lee (1976), looming is defined here as:

$$\tau^{-1} = \frac{\dot{\theta}}{\theta}, \tag{3.5}$$

where $\theta$ is the optical width of the lead vehicle (but could, in principle, be the angle between any two simultaneously observable points on the vehicle). Due to the equivalence with TTC, $\tau^{-1}$ is a well-established measure of looming in critical driving situations (Boda et al., 2020; Kondoh et al., 2014; Markkula

et al., 2016; Morando et al., 2016; Summala et al., 1998; Terry et al., 2008; Xue et al., 2022). Notably, other looming definitions such as $\dot{\theta}$ (Liebermann et al., 1995; Mortimer, 1990) and $\frac{v}{\tau}$ (Fajen, 2005; R. J. Kiefer et al., 2005; R. Kiefer et al., 2003) have been used as well (though the latter appears to be more suitable to describing routine driving than critical situations; Markkula et al., 2016).

The driver is assumed to collect evidence (i.e., looming) of braking over time. This evidence is continuously compared to the driver's prediction about how the sensory input will develop over time (i.e., prediction of future sensory input), with the difference forming a perceptual prediction error. Noise is added to the prediction error, and the resulting quantity is accumulated until an arbitrary activation threshold is reached. Surpassing the threshold triggers (1) a reset of the accumulated error, (2) the onset of an adjusting control action, and (3) an update of the (low-level) prediction of sensory inputs based on the control action. The magnitude of the control action is scaled to the situational urgency as a multiple of the prediction error. In the suggested braking models, the scaling corresponds to the brake jerk's adaptation to the judged severity of the situation (i.e., braking harder the more critical the situation is perceived to be, causing a faster deceleration ramp-up).

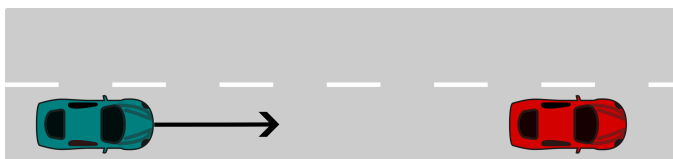

**Figure 3.2:** An illustration of a critical lead vehicle situation. The modeled driver is in the teal-colored car. The red lead car is stationary or decelerating, which eventually causes the modeled driver to brake.

The generic framework also allows the inclusion of other evidence for or against a control action; see Figure 3.3. Additional evidence could, for example, be the driver's internal expectations about the upcoming traffic situation or the onset of a forward collision warning. In the braking model presented in Paper 3, a constant gating factor is subtracted from the predictor error, representing (in a simplified manner) all non-looming evidence.

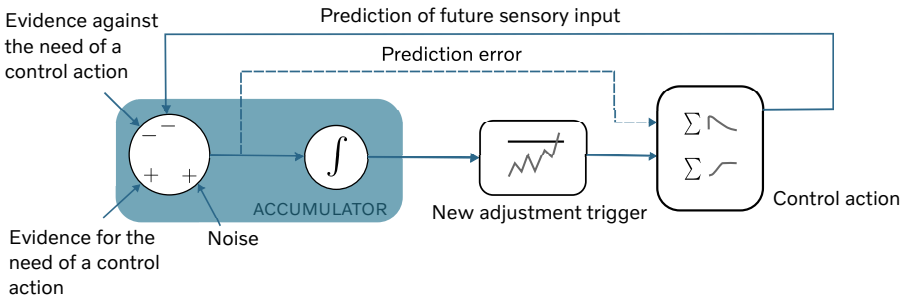


**Figure 3.3:** An overview of the computational model framework based on predictive processing and noisy evidence accumulation.

## Bayesian linear regression

The Bayesian statistical framework is becoming increasingly popular. One of the reasons is the advancement of simulation methods which do not require closed-form analytical expressions for the posterior distributions. Bayesian statistics is based on Baye's theorem, which states the probability of an event given previous knowledge. Consequently, a key difference between frequentist and Bayesian statistics is the possibility to incorporate prior beliefs into the models (see, e.g., Koch, 2007 or Lambert, 2018 for an introduction to Bayesian statistics).

In contrast to frequentist analysis, Bayesian statistics represents an intuitive interpretation of statistical concepts. It may also be less prone to misinterpretation (e.g., the interpretation of the frequentist $p$-value is widely disputed in the literature; see the discussion by J. Kim & Bang, 2016). Although similar to traditional regression methods (especially with the use of non-informative or vague priors, representing no, or very little, prior knowledge), Bayesian regression provides the posterior distributions of the predictor parameter values. These distributions are much more informative than the mere single numerical estimate (possibly with a confidence interval and $p$-value) yielded by the frequentist approach (Lambert, 2018).

The Bayesian regression techniques used in Papers 4 and 6 are based on two main assumptions: (1) the prior distributions of predictor coefficients are normal and non-informative, (2) the posterior distribution of the model output is normal, with the mean as a linear combination of the predictor variables. The posterior distribution of the model parameters is generated by a Markov

chain and Monte Carlo simulations, using the Markov Chain Monte Carlo (MCMC) computational method (Koch, 2007). Each posterior parameter distribution is associated with a highest posterior density (HPD) interval, corresponding to the shortest interval covering a certain percentage of the total probability density (in this thesis, 95 %; see Figure 3.4). If an HPD interval does not overlap with zero or with a predefined region of practical equivalence (ROPE; see Figure 3.4), the corresponding parameter can be considered to contribute significantly to the model fit (Hespanhol et al., 2019). The use of a ROPE is optional, but it allows significance to be defined more conservatively, since it considers a whole range of values to be practically equivalent to the null value (Kruschke, 2018). A ROPE was used in Paper 4 but disregarded in the model selection process of Paper 6.

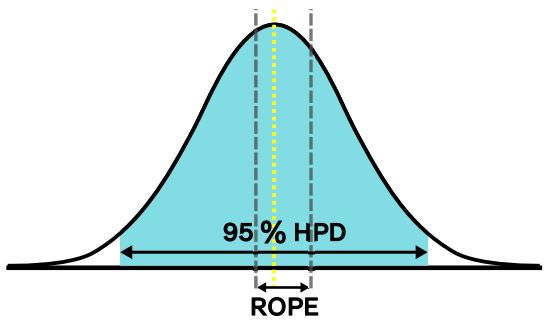


**Figure 3.4:** Illustration of a posterior distribution. The blue area depicts the 95 % HPD interval; the ROPE lies between the two dashed lines. Note that the ROPE is not necessarily symmetric around zero (yellow, dotted line).

## 3.3 Parameter estimation

Once the basic model structure is set, accurate estimations of the model parameters are essential for satisfactory model performance. In some cases, using different parameter sets for different model application areas may be beneficial, or even necessary. For example, one set of parameters may be applied to an evasive-braking model to evaluate the average driver performance in a virtual safety benefit assessment. On the other hand, a completely different

parameter set may be appropriate when the same model is used to describe the braking behavior of an alert and attentive driver in order to set safety targets for AD vehicles. For most use cases, offline estimation can be used a priori to determine the optimal model parameters. However, the parameter values must continuously be updated using online (recursive) parameter identification methods when the objective is to tune an ADAS to the current driver.

## Offline parameter estimation

Offline parameter estimation methods assume all data to be known, and thus, at each sample, they consider both previously observed and upcoming (yet to be seen) data. Consequently, the resulting parameter set is optimized to reflect the average data trends. The choice of estimation method depends on the model structure and its complexity. This thesis used both conventional prediction error methods and stochastic optimization methods, as described below.

### Prediction Error Method (PEM)

The PEM (see, e.g., Ljung, 1999) estimates the predictive performance of a model and is applicable to both offline and online parameter estimation. In its general form, PEM solves the following problem:

$$\begin{aligned} \hat{\theta} &= \arg\min_{\theta} \epsilon\left(\theta\right), \\ \epsilon\left(\theta\right) &= \frac{1}{N}\sum_{k=1}^{N} l\left(y_k - \hat{y_k}\left(\theta\right)\right), \end{aligned} \tag{3.6}$$

where $y_k$ is the observed data, and $\hat{y_k}(\theta)$ is the model estimate at the $k^{th}$ sample, calculated using the parameter set $\theta$. In this thesis, $l\left(y_k - \hat{y_k}\left(\theta\right)\right) = \left(y_k - \hat{y_k}\left(\theta\right)\right)^2$, which corresponds to least squares estimation (Ljung, 1999).

### Particle Swarm Optimization (PSO)

Due to the complexity of the computational driver models discussed in this thesis, the conditions ensuring that conventional optimization methods (the gradient descent algorithm, for example) converge to a global optimum are

rarely fulfilled. Instead, stochastic optimization methods, such as the population-based PSO method (see, e.g., Wahde, 2008; Y. Zhang et al., 2015), may be more appropriate. Stochastic optimization methods are particularly suited for searching vast solution spaces. Although these methods also cannot guarantee global optimality of the estimated parameters, the optimization performance is generally sufficient for driver model applications.

In the PSO method, a swarm of particles searches the solution space to find the optimal solution to a parameter identification problem. Each particle corresponds to a potential model parameter set. The particle velocities are updated in each iteration, and each particle accelerates towards a linear combination of its best position from previous iterations and the global best position (the hitherto best position of any particle in the swarm). Performance-dependent fitness values are assigned to each particle to guide the search. The fitness values are usually based on the difference between the observed data and the model output (which what obtained by applying the parameter set corresponding to the current particle position in the search space).

### Maximum likelihood estimation (MLE) through kernel density estimation (KDE)

Estimating the parameter values of driver models that include a stochasticity component (noise) adds a level of complexity compared to estimating the parameter values of deterministic models, since the output will vary for the same set of parameters. A feasible approach to manage the added complexity is resorting to Monte Carlo simulations to generate a distribution of the model performance corresponding to each parameter set, instead of a single performance measure. Likelihood-based methods can then be used to compare the performance distributions and find the best parameter set (see, e.g., Rice, 2007, for a fuller explanation).

MLE identifies the model parameter set $\hat{\theta}$ which maximizes the likelihood $\mathcal{L}(\theta \mid y)$ that the given model generated the observed data points $y$:

$$\hat{\theta} = \arg\max_{\theta} \mathcal{L}\left(\theta \mid y\right). \tag{3.7}$$

Since a multivariate probability distribution (pdf) of the chosen performance measures is generated (in Paper 4, a distribution of brake initiation times and brake jerk levels), the total likelihood of the Monte Carlo simulations can be

evaluated. Consequently, MLE can be used to estimate the model parameters. When no closed form of the pdf is available, and only a limited set of actual observations are made, the pdf can be approximated using KDE (see, e.g., Węglarczyk, 2018). KDE uses data smoothing of a finite data set, by applying potentially overlapping kernel functions (in Paper 4, Gaussian functions) to the observed data points. The performance measures can be weighted according to their relative importance using separate kernel standard deviations for each dimension.

## Online parameter estimation

Online parameter estimation identifies model parameters by recursively including newly observed data samples into the dataset. The available data points can be unevenly weighted to favor newer data over old data and thus accurately represent the *current* driving behavior (rather than the behavior reflected in the old observations). In this thesis, a sliding window continuously updates the estimated parameter values based on only the most recent data samples (thus completely discarding old samples). At the time $t$ of each new observation, a weighting factor $\beta(t,k)$ is assigned to all past observations $k = 1, 2, ..., n_t$. The weighting factor is assigned a binary value:

$$\beta(t,k) = \begin{cases} 0, & t_k < t - \tau \\ 1, & t_k >= t - \tau, \end{cases} \tag{3.8}$$

where $\tau$ is the length (in time) of the sliding window.

In this thesis, online parameter estimation is performed by combining a sliding window with PEM (see Section 3.3). The following problem is solved for each new discrete observation at time $t$:

$$\begin{aligned} \hat{\theta} &= \arg\min_{\theta} \epsilon\left(t,\theta\right), \\ \epsilon\left(t,\theta\right) &= \frac{1}{N_\tau} \sum_{k=t-\tau}^{t} \left(y_k - \hat{y_k}\left(\theta\right)\right)^2, \end{aligned} \tag{3.9}$$

where $N_\tau$ is the number of samples in the sliding window. Note that reliable parameter estimates require excitation of the model-relevant signals, a condition not fulfilled at all instants during driving. This problem can be overcome by using kinematics-dependent window lengths or by disregarding

low-excitation data. Paper 1 adopts the latter approach.

### Levenberg-Marquardt (LM) algorithm

The LM algorithm (Levenberg, 1944; Marquardt, 1963) is a stable, efficient method for solving non-linear least squares problems and is thus a suitable choice to solve the PEM problem formulated in Equation 3.9 when the model is non-linear. It is a numerical, iterative optimization algorithm similar to the Gauss-Newton algorithm (Levenberg, 1944). Given an initial guess for the parameter vector $\theta$, the LM algorithm incrementally updates the parameter estimates by adding an increment $\delta$. In contrast to the Gauss-Newton algorithm, a damping parameter $\lambda$ scales the gradient according to the current curvature (i.e., larger increments for small gradients). The increment $\delta$ is found by solving the following equation (Fletcher, 1971):

$$\left(\mathbf{J}^T\mathbf{J} + \lambda \mathrm{diag}\left(\mathbf{J}^T\mathbf{J}\right)\right)\delta = \mathbf{J}^T\left[\mathbf{y} - \hat{\mathbf{y}}\left(\theta\right)\right], \tag{3.10}$$

where $\mathbf{J}$ is the Jacobian matrix of $(\mathbf{y} - \hat{\mathbf{y}}(\theta))$, $\mathbf{y}$ is the vector of observed data points, and $\hat{\mathbf{y}}(\theta)$ is the estimated model output using the parameter vector $\theta$. The damping factor is dynamic and may be updated during the optimization process. A small damping value corresponds to a Gauss-Newton parameter update, while a large value results in a parameter update according to the steepest descent method (Fletcher, 1971).

## 3.4 Driver model application in simulation

Computational driver behavior models constitute an essential part of virtual safety assessments. However, the accuracy of the final results are also heavily dependent on the rest of the simulation environment. Essential parts of the simulation environment include, for example, how the vehicle dynamics are modeled, how accurate and representative the simulated scenarios are (in scenario-based assessments), and how realistic the traffic environment setup is, in terms of both infrastructure and the behavior of other road users.

The driver models in Papers 3 and 4 have been applied in scenario-based counterfactual simulations. A simulation tool with basic vehicle dynamics was used to recreate the dynamics of crashes and near-crashes present in NDD from SHRP2 in a virtual environment (Paper 4) and to evaluate the driving

performance in standardized lead vehicle scenarios created by Euro NCAP (Paper 3). Paper 4 uses NDD with recorded driver behavior to estimate the parameters of a set of driver models. The model performance is compared to the observed human behavior in the same situation (in the NDD). Removal of the human evasive maneuver in the recorded data before the driver model application was necessary to separate the actual human behavior from the model-generated control output. One way to remove the maneuver is by first identifying its start and then assuming that the driver keeps a constant speed until the driver model starts braking (Bärgman, Boda, & Dozza, 2017), as illustrated in Figure 3.5.

In addition to being used in parameter estimation, evasive maneuver removal is an efficient tool in scenario-based prospective safety assessments, when a driver model replaces the original driver reaction in a certain scenario (e.g., to evaluate the potential effect of a warning system (Bärgman, Boda, & Dozza, 2017; Seyedi et al., 2021; Sugimoto & Sauer, 2005). However, this approach is not necessary in multi-agent traffic simulations since those are based entirely on virtual drivers (instead of recorded or reconstructed crash data), with all the benefits and drawbacks associated with that way of generating safety-critical situations.

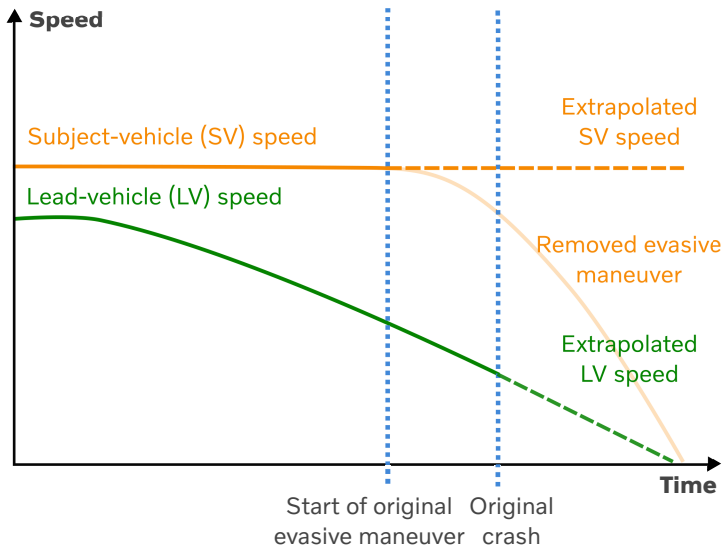


**Figure 3.5:** Example of speed profiles before and after removing the original evasive (braking) maneuver. The blue, dotted lines mark the start and end (i.e., the crash point) of the original evasive maneuver. The maneuver is removed by extrapolating the subject-vehicle's prior speed (orange line). Note that the lead vehicle speed (green line) is extrapolated after the crash point in case the counterfactual simulation results in a scenario that is longer than the original.

# CHAPTER 4

# Summary of included papers

This chapter provides a summary of the included papers.

## 4.1 Paper 1

### Online driver behavior classification using probabilistic ARX models

Malin Sundbom, Paulo Falcone, and Jonas Sjöberg (2013).

**Background:** In-vehicle ADASs are generally not adapting their intervention and warning thresholds to the individual drivers. Hybrid models are promising for capturing drivers' capabilities and predicting driver behavior in real time.

**Aim:** This study used the hybrid ARX driver modeling framework with the main aim of classifying the driver's current driving style and predicting the driver's steering behavior.

**Method:** A two-mode PrARX model for steering was suggested: (1) normal driving and (2) aggressive driving. The model parameters were estimated online through a prediction error method using particle swarm optimization and the Levenberg-Marquardt algorithm to set the initial parameter values. The model was validated on data collected from a small test track study.

**Results:** The suggested driver model showed good performance in distinguishing between normal and aggressive driving on curved road segments (the relevant sensitivity and specificity were approximately 90 %). Moreover, it could accurately predict the driver's steering angle one time step ahead. Lateral acceleration and movement in the lane had the most substantial influence on the model predictions.

**Discussion:** Incorporating the suggested driver model into the threat assessment and decision-making layer of an ADAS would allow the system to adapt to the current driver. For example, lane departure warnings could be suppressed more than usual for drivers exhibiting an aggressive driving style.

## 4.2 Paper 2

### A study of appropriate model complexity for estimation of car-following behavior

Malin Sundbom and Jonas Sjöberg (2015).

**Background:** Driver models of routine car-following behavior could be used to automatically adapt a forward collision warning and avoidance system to individual drivers. However, routine driving may not contain enough informative data to motivate high-complexity models.

**Aim:** This paper aimed to investigate possible model structures for predicting and classifying drivers' car-following behaviors and to analyze to what extent complex models could be justified.

**Method:** Dynamical longitudinal control models based on the hybrid ARX framework were systematically investigated and compared to simpler model structures. The models predicted the drivers' pedal operation during car-following and classified whether the drivers were in a "safe" or "dangerous" driving mode (with the dangerous mode indicating that the current driver usually would have braked in the given kinematic situation). The models were applied to data from a driving simulator experiment with five participants performing a car-following task on an expressway. A prediction error method was used for the parameter estimation.

**Results:** Complex model structures could not be justified for long prediction horizons (more than one time step), since the predictive performance was not better than for simpler model structures. However, the complex models could be used to accurately classify whether the driver sensed an upcoming need to brake. Simple classification models were not as precise.

**Discussion:** Car-following driver models with simple structures may perform better than their complex counterparts. More informative data (i.e., not just from highway driving) would be necessary to justify complex models.

## 4.3 Paper 3

### A quantitative driver model of pre-crash brake onset and control

Malin Svärd, Gustav Markkula, Johan Engström, Fredrik Granum, and Jonas Bärgman (2017).

**Background:** Understanding drivers' responses in critical situations is essential for road safety benefit estimation. Many traditional emergency braking models focus on probability distributions of reaction times and assume predefined braking profiles. A model framework based on ideas from ecological psychology may lead to models that are more generic and (neurologically) accurate.

**Aim:** The aim of this paper was to apply a previously suggested computation framework for driver control behavior to create a model of drivers' braking behaviors in critical lead vehicle scenarios.

**Method:** A computational framework based on predicitve processing and noisy evidence accumulation was used to design a driver model for emergency braking. The manually tuned model was combined with a glance behavior distribution and used to simulate a set of lead vehicle scenarios designed by Euro NCAP. The outcomes, in terms of brake initiation time and brake jerk, were compared to naturalistic driving data (SHRP2).

**Results:** A comparison of the simulation output and naturalistic driving data led to the conclusion that the suggested driver model produced qualitatively realistic, kinematics-dependent brake initiation times and brake jerk values.

**Discussion:** The computational driver modeling framework used in this paper is generic and can be adapted to other situations than lead vehicle critical scenarios. It is also possible to include driver expectancy in the models, forming a solid base to build models describing driver behavior in relation to, for example, failing automation systems.

## 4.4 Paper 4

### Computational modeling of driver pre-crash brake response, with and without off-road glances: Parameterization using real-world crashes and near-crashes

Malin Svärd, Gustav Markkula, Jonas Bärgman, and Trent Victor (2021).

**Background:** Sufficiently validated computational driver models for brake modulation which take driver eye movements into account are currently lacking. Capturing how specific traffic situations and gaze patterns influence the driver's response process would be valuable for virtual safety benefit estimations.

**Aim:** The main aim of this work was to determine how off-road glance behavior could be included in a driver model for critical longitudinal scenarios. Another aim was to thoroughly parameterize a driver model using naturalistic data from real-world crashes and near-crashes for the first time.

**Method:** An existing model for driver brake initiation and modulation was extended and fitted to naturalistic driving data, using a stringent method for parameterization and model selection based on particle swarm optimization and maximum likelihood estimation. The model parameters were calculated on four partly overlapping data sets of progressively more severe lead vehicle events.

**Results:** The results indicate that drivers have partial perception of looming while looking off-road, and that reduced responsiveness to looming may be an important crash-causation factor. Moreover, the results showed that models parameterized on less-critical data could successfully reproduce driver behavior in highly critical events.

**Discussion:** This paper successfully demonstrate how to fit a driver behavior model to real-world crash and near-crash data, considering that evidence accumulation can occur also during off-road glances. Using this kind of model in virtual safety evaluations ensures a high level of representativeness in the results.

## 4.5 Paper 5

### Detection and response to critical lead vehicle deceleration events with peripheral vision: Glance response times are independent of visual eccentricity

Malin Svärd, Jonas Bärgman, and Trent Victor (2021).

**Background:** An essential part of preventing crashes caused by visual distraction is understanding drivers' use of peripheral vision to detect and react to threats. This area is often overlooked in driver behavior models.

**Aim:** The main aim of this work was to quantify the driver's use of peripheral vision to accumulate perceptual evidence of a decelerating lead vehicle, which then contributes to the computational modeling of driver response processes in critical lead vehicle scenarios.

**Method:** A between-group experiment with 83 participants was performed in a high-fidelity, moving-base simulator. The participants were exposed to the sudden, severe braking of a lead vehicle on a two-lane, divided highway while performing a distraction task. The effects of horizontal visual eccentricity angle (12°, 40°, or 60°) on threat detection, glance, and brake response times were analyzed.

**Results:** Drivers' glance response times were independent of the visual eccentricity angle. However, the brake response times increased with increasing eccentricity of the distraction task. Moreover, large angles were associated with low threat-detection rates and frequent on-road check glances.

**Discussion:** The results indicate that drivers use peripheral vision to collect evidence for braking during off-road glances. This insight may be used to extend existing models of human braking behavior in critical scenarios in order to improve the representativeness of virtual simulation results.

## 4.6 Paper 6

### Using naturalistic and driving simulator data to model driver responses to unintentional lane departures

Malin Svärd, Gustav Markkula, Mikael Ljung Aust, and Jonas Bärgman (*submitted*).

**Background:** Computational models of drivers' responses to critical lane departure events are a prerequisite for performing realistic virtual safety evaluations involving such events. However, models of this kind are currently lacking.

**Aim:** This work aimed to investigate and model drivers' corrective steering responses during unintended lane departure events. The driver repsonse was assessed in terms of steering amplitude and timing.

**Method:** Steering responses from three different lane departure data sets were investigated, with steering quantified as yaw rate relative to the road heading. Steering initiation times were reported as response time distributions in relation to the last off-road glance before the steering initiation. Steering amplitude models based on a set of lane departure risk metrics were fitted to the data using Bayesian linear regression.

**Results:** In many cases, the corrective steering adjustment was initiated before, or at the same time as, the driver's glance was redirected to the forward roadway. The correction amplitude was successfully modeled using a polynomial model of the relative yaw angle at steering initiation. The model outperformed alternative models based on more complex risk metrics. However, for the naturalistic data sets, the change in splay error was a better predictor than the relative yaw angle.

**Discussion:** The results indicate that drivers can use peripheral visual information to guide their steering responses. However, further studies to investigate influences on the steering amplitude, and how these may differ depending on the data source, would be warranted.

# CHAPTER 5

# Discussion

This chapter addresses the most critical aspects of the appended papers and gives an overview of the practical implications of the findings. Sections 5.1–5.3 frame the main results in relation to the general research questions, as formulated in Section 1.1. This is followed by some brief remarks on the potential of using cognitive models for ADAS tuning. Finally, the major limitations of the thesis work are highlighted, together with an outlook on future research needs in the area of computational driver modeling.

## 5.1 Real-time estimation of driving behavior for online tuning of ADAS

Real-time, continuously updated computational driver models show great potential to improve ADAS performance by reducing the number of undesired warnings, and, possibly, increasing number of the warnings for unskilled or novice drivers. Two main approaches for improving ADASs have been identified: time-series prediction of driver behavior and driver behavior classification. Both approaches are discussed in more detail below.

## Online prediction of driving behavior

The results in Paper 1 and Paper 2 suggest that prediction models based on a hybrid ARX framework can be used to measure or detect variability in driver behavior over time, as long as proper signal excitation is ensured. PrARX models were shown to make accurate time series predictions of both steering control and pedal usage during routine driving.

In Paper 1, lateral control was modeled using the vehicle's lateral acceleration and yaw rate, the absolute value of the lateral movement in the lane, and the absolute value of the heading error. Yaw rate emerged as the most important predictor variable, which was to be expected since the steering angle is closely coupled to the yaw rate (and vehicle speed; Pacejka, 2006). Since the selected predictors were exclusively based on the vehicle's yaw angle and lateral movement in the lane, the regressor did not contain enough information to predict the driver's steering behavior on straight roads. Nonetheless, a high level of prediction accuracy was reached when enforcing a curvature threshold on the prediction algorithm (equivalent to discarding input with little or no excitation). ADASs relying on this type of driver model should thus take road curvature into account and be recommended not to trust predictions based on data collected on road segments with low excitation levels of the relevant signals (e.g., on straight roads).

As for the longitudinal control domain, Paper 2 evaluated the predictive performance of models of various degrees of complexity. All models were based on the range (relative distance to a lead vehicle), the range rate (speed relative to a lead vehicle), and the KdB risk index. The KdB risk index corresponds to the change in area of the visual image of the lead vehicle on the observer's retina and is thus a measure comparable to visual looming (Wada et al., 2007). The analysis concluded that satisfactory prediction performance was difficult to achieve when predicting driver behavior over long time horizons. In fact, simple model structures performed as well as their more complex counterparts for prediction horizons exceeding one time step.

Information from other systems, for example the DMS, could complement the online driver models and improve the prediction accuracy (Hayley et al., 2021). Black-box models, which were beyond the scope of this thesis, could potentially also perform better than the models presented in Papers 1–2. However, these have the drawbacks of requiring extensive computational power, being sensitive to the quality and amount of training data, and are usually

hard to interpret (Linardatos et al., 2021). A more feasible alternative could be applying the suggested driver models to real-time classification of driving style rather than to a detailed prediction of the driver's control behavior.

## Online classification of driving behavior

Behavioral classification into clusters, or modes, with mutual similarities can be used to differentiate between various driving styles—or to identify whether drivers are driving within their individual safety limits. Both the current mode affiliation and mode boundaries are subject to change over time. An HDS can describe the dynamics in each mode and the switching between modes (Akita et al., 2007a; Okuda, Ikami, et al., 2013). Although black-box models are becoming increasingly popular for real-time driver model applications (Elamrani Abou Elassad et al., 2020), hybrid ARX models can also be used for classification purposes (Taguchi et al., 2009).

Keeping the hybrid ARX framework for driving behavior classification has several advantages: it is possibile to perform both classification and prediction simultaneously; it is suitable for online parameter estimation; and it facilitates an intuitive understanding, and thus a more relevant analysis, of model mechanisms. PrARX models were used to demonstrate a method for lateral driving style estimation (Paper 1) and to determine whether the driver is currently driving within his or her comfort boundaries (Paper 2). The drivers were assumed to operate in the mode related to the highest estimated probability. A similar approach has previously been demonstrated by Ikami et al. (2011); see Section 3.2.

The classification potential of PrARX models was demonstrated in Paper 1. The model was designed to distinguish between predominantly aggressive driving and non-aggressive driving. Aggressive driving is commonly described as inappropriate, or even hostile; it has received a great deal of attention due to the drivers' risk-taking behaviors (Persak, 2011; Quintero M. et al., 2012; Sagberg et al., 2015; Shinar, 2017; Su et al., 2023). This description was somewhat relaxed in Paper 1, where a tendency toward high lateral acceleration and a wide range of lateral movement in the lane characterized the aggressive driving mode. Although the suggested classification model requires curved road segments for necessary signal excitation, it was shown to perform well in such environments. It should be safe to assume that, in most cases, the general driving style will not abruptly change from aggressive to non-aggressive.

Thus, the driving style can be expected to remain in the latest estimated mode for some time when the driver enters occasional straight road segments.

Drivers' emotions have been suggested to influence their adopted driving style (Eboli et al., 2017; Habibifar & Salmanzadeh, 2022). Recent publications have analyzed how the driver's affective state relates to driving performance and how changes in the driver's mood can be identified (Braun et al., 2020; Jeon, 2012; Jeon et al., 2014; Lopez-Martinez et al., 2019). A personalized, adaptive FCW system based on affective state estimation has even been proposed (Govindarajan et al., 2018). The authors report that the adaptive system improves the warning precision with 40–50 %, and the warning accuracy with approximately 10 %, compared to conventional FCW systems. Fusing information about the driver's affective state and estimated driving style may result in more robust classification systems, since the information generated by one subsystem (e.g., affective state estimation) can complement the other (e.g., driving style estimation). Such complementarity may be particularly beneficial when the accuracy of the driving style classification algorithm is low, such as on straight road segments (for most driving style classification models) or in absence of other road users (for car-following models).

ADASs could use information about driving style for real-time tuning of warnings and intervention thresholds. For example, lane departure warnings and steering interventions may be more frequently delayed or suppressed for an aggressive driver. On the other hand, if the system "knows" that the driver does not usually drive aggressively, it could enable valuable interventions, such as when drivers accidentally exceed the lane boundaries in situations where commercial LKS warnings and interventions are generally suppressed (e.g., in sharp inner curves). Research has, however, shown a correlation between aggressive or hostile driving styles and crash risk, which can partly be explained by an elevated tendency to violate traffic rules (Sagberg et al., 2015). Consequently, care should be taken when determining which warnings and interventions should be suppressed.

Whereas the driving style identification model presented in Paper 1 can potentially improve ADASs, it is arguably mainly beneficial for systems targeting lateral situations, such as lane departures. In a situation with a threat in the longitudinal direction, such as a slower or decelerating lead vehicle, it might be better to use driver classification models to detect when drivers are unaware of, or unprepared for, a critical situation (i.e., leaving a "safe"

driving mode). In Paper 2, a PrARX model with simplified mode transition was suggested to distinguish between safe and unsafe car-following behavior. In this model, patterns of the driver's previous brake and throttle pedal operation were used as inputs. Akita et al. (2007a, 2007b) investigated a similar concept, modeling pedal operation as a piecewise ARX model. Driving control was divided into four modes, one of which corresponded to longitudinal collision avoidance behavior. The optimal number of modes, arguably depending on the intended model application, could also be determined based on a trade-off between model robustness and model error, as discussed by Nwadiuto et al. (2021). Nwadiuto and colleagues suggest applying an iterative submodel selection method, based on the Bayesian Information Criterion, to PWARX models in order to balance model accuracy against model complexity (i.e., model error against robustness, since the model complexity influences how well the model generalizes to unseen data).

By continuously collecting driving data and updating the classification model parameters in real-time, ADASs that target longitudinal situations (e.g., FCW or AEB systems) can be tailored to the current driver's comfort zone. Such a system would only warn or intervene when the driver remains in the non-braking mode as a threatening situation arises. Consequently, this kind of model would improve ADASs in the same way as the driving style classification discussed above: reducing undesired interventions and enabling earlier warnings for unskilled drivers. Importantly, the threshold of the system's perception of dangerous situations must be set at a suitable level. Note, however, that if the ADAS detects a threat that the driver has very little chance of avoiding by braking or steering (or a combination thereof) an intervention must be issued even if the driver is estimated to be prepared to brake. This kind of late intervention is critical for reducing the negative impact of classification errors in severely critical situations, as well as for mitigating the risk that the driver will apply insufficient brake pressure; the classification model does not specify the expected deceleration amplitude.

While the framework used in this thesis had great potential (and still does), recent research has turned more towards machine learning and statistical modeling as the availability, amount and quality of data suitable for model training are constantly increasing (see, e.g., the reviews by Elamrani Abou Elassad et al., 2020 and Yi et al., 2020). Similar to the method suggested in Paper 1, these models are either trained offline or require a calibration period to ob-

tain a reasonable initial estimate of the model's parameter values. These values are then updated by online algorithms. Lately, methods facilitating the interpretation of ML models through explainable artificial intelligence have emerged (Gunning & Aha, 2019; Linardatos et al., 2021), and advances have been made in real-time driver modeling applications, using a variety of HMM structures in combination with autoregressive (AR) models (Akai et al., 2019; Hamada et al., 2016; Jain et al., 2015). This approach is similar to the hybrid ARX framework. Nonetheless, the model interpretability is still higher for conventional HDSs (including hybrid ARX models), and these thus remain reasonable alternatives to statistical models. One of the main drawbacks of HDSs is that the number of modes must be predetermined, but efforts have been made to solve this issue by suggesting methods for automatic mode segmentation (Nwadiuto et al., 2021).

Personalized systems are still rare. According to Hasenjäger et al. (2020), only a single prototype system had been implemented in a physical vehicle by 2020: an adaptive longitudinal ADAS (J. Wang et al., 2013). Nevertheless, simulator studies show a clear advantage for personalized ADASs over conventional ADASs, in terms of successful interventions (Lefèvre et al., 2015) and false warnings (J. Wang et al., 2016). Several attempts to construct driver-adaptive ADASs have been made, targeting systems such as FCW (J. Wang et al., 2016), AEB (Muehlfeld et al., 2013), LKS (Lefèvre et al., 2014, 2015; W. Wang, Zhao, et al., 2018), ACC (Bifulco et al., 2013; Lefèvre et al., 2015, 2016; J. Wang et al., 2013; Zhao et al., 2022), and automatic lane change systems (Butakov & Ioannou, 2015; Vallon et al., 2017). However, more research is needed to determine how best to design and integrate these systems into the vehicle (see, e.g., the survey by Hasenjäger et al., 2020 or the review by Yi et al., 2020).

Apart from allowing real-time ADAS adaptation, driver classification models have the potential to increase road safety by enabling driver monitoring in vehicle fleets. For instance, identifying drivers' dominant driving styles (by calculating the percent of driving spent in the aggressive driving mode using the method proposed in Paper 1) makes it possible for insurance companies to adapt their fees according to the crash risk associated with that driving style. This action might incentivize drivers to adopt to safer driving patterns (similar to the behavior-based monitoring systems proposed by Horrey et al., 2012; Sekar et al., 2014; and Toledo et al. 2008). If granted permission

to access relevant data, road authorities could also benefit from driver classification models, which might identify certain road areas where drivers often leave their comfort zones.

## 5.2 Computational modeling of driver behavior in critical situations

Drivers may encounter a wide variety of potentially threatening situations, all putting different demands on the driver's response. Hence, it is common to constrain computational driver models so they are valid only for specific traffic situations (see, e.g., the review by Markkula et al., 2012b). This thesis targets drivers' evasive maneuvers in two of the most common road conflicts: collisions with a lead vehicle and unintentional lane departures. In the former, drivers typically brake to resolve the conflict (Adams, 1994; Ljung Aust et al., 2013), though steering is also possible (but beyond the scope of this thesis). In contrast, the latter situation warrants an evasive steering maneuver to safely return to the roadway. Driver models tailored for each of these scenarios are further discussed below.

### Lead vehicle collision avoidance by braking

Papers 3–4 challenge the traditional modeling paradigm which initiates braking based on reaction time distributions and predetermined trigger mechanisms (e.g., the onset of lead vehicle brake lights or a looming threshold; Delorme & Song, 2001; D. N. Lee, 1976; Shinar et al., 1997; Society of Automotive Engineers, 2015). The papers present an approach more consistent with the state of the art in cognitive science and neuroscience. The suggested models are based on noisy evidence accumulation of a visually perceivable quantity (looming; D. N. Lee, 1976) and ideas from predictive processing (Clark, 2013, 2015).

In addition to being cognitively plausible, the framework used in Papers 3 and 4 allows great flexibility in the model setup. The flexibility is reflected in the possibility of including additional model layers (e.g., the high-level prediction layer mentioned in Paper 3) and adapting the included components to fit different modeling needs (e.g., to consider different kinds of critical scenarios or evasive maneuvers; Engström et al., 2022; Engström, Bärgman, et al., 2018;

Markkula et al., 2018). Paper 3 describes the construction and validation of a non-deterministic, kinematics-dependent model for brake initiation and modulation intended for critical lead vehicle scenarios. The possibility of an additional (high-level) prediction layer means that the suggested model can be extended to account for the driver's current beliefs and expectations about an upcoming situation.(See Engström, Bärgman, et al., 2018 for a more substantial discussion on how to interpret the high-level prediction layer.) High-level prediction was further investigated by Bianchi Piccinini et al. (2020), who used it to model drivers' responses to silent automation failures, based on the model suggested in Paper 3. In Paper 3, instead of including a prediction layer to account for overall driver expectancy, it is accounted for (at least partly) by scaling the prediction error by a certain gain, then adding a gating parameter before the accumulation. Here, the gating term represents the sum of all non-looming evidence for or against braking.

Paper 4 further extends the model in Paper 3 with parameters to account for the driver's gaze direction, current cognitive state and evidence decay. Multiple model variants are explored to evaluate the effect of including different combinations of these additional parameters. In some of the suggested model variants, the gaze direction is accounted for by assuming that the drivers can perceive looming partially even when (foveally) looking off-road. The validation and implication of this assumption is further discussed in Section 5.3.

The driver's cognitive state has been found to influence the expectations about the upcoming situation or reduce the responsiveness to looming and other perceptual inputs (Y.-C. Lee et al., 2009; Ratcliff & Van Dongen, 2011). Further, studies have associated factors such as driving style and driver impairment, which can be reflected in the cognitive state, with increased crash risk (Dingus et al., 2016; Nilsson, 2022). In Paper 4, the driver's cognitive statee was estimated based on the pre-crash gaze pattern. A distinction was made between events in which drivers kept their gaze directed toward the forward roadway and events in which they performed visual time-sharing between the road in front and other areas of interest (e.g., secondary tasks). This separation was motivated by the mechanisms causing a situation to become critical, which are different for eyes-on-road and eyes-off-road events. In eyes-on-road events, a mismatch between the driver's expectations and the upcoming situation is a more important factor than it is in eyes-off-road events (Engström, Bärgman, et al., 2018; T. W. Victor et al., 2018), since the latter are mainly

caused by ill-timed off-road glances (Markkula et al., 2016; T. Victor et al., 2015). The expectation mismatch was, in this case, modeled as a decreased sensitivity to looming in eyes-on-road events—the prediction error was scaled with a lower gain than eyes-off-road cases. However, the same decrease in prediction error could have been achieved by including the high-level perception prediction layer described in Paper 3 (as suggested by Engström, Bärgman, et al., 2018).

The final model addition described in Paper 4 was evidence decay, which was integrated by adding a leakage term in the accumulation, thus allowing the models to emphasize newly acquired sensory input over old (Nunes & Gurney, 2016; Usher & McClelland, 2001). The idea of leakage in accumulator models was applied by Usher and McClelland (2001) to achieve a soft truncation (i.e., gradual forgetting) of the accumulated information. This method differs from to the hard truncation achieved with a model that immediately discards input accumulated outside a particular time frame. (Hard truncation was used in the sliding window estimation method applied in Paper 1; see Section 3.3.) The concept of soft truncation is aligned with the theory of (memory) decay first suggested by Thorndike (1913), which assumes a gradual decrease in synaptic strengths as a result of neuron inactivity (see also J. Brown, 1958). Paper 4 shows that the performance of the braking models significantly improves when the models are allowed to "forget" old looming input. Moreover, the Adaptive Control of Thought-Rational (ACT-R) model for driving, suggested by Salvucci (2006), incorporates a similar activation decay mechanism, which also allows the model to predict potential driver errors caused by acting on outdated information (errors which could occur if the model did not perform a visual scanning of the environment often enough).

The ACT-R architecture also considers the driver's cognitive state, and effects of driver sleepiness have previously been modeled in this architecture as cognitive microlapses. The microlapses result in *fluctuations* in the driver's cognitive capacity (perceptual responsiveness), rather than a decrease, which causes response delays (Gunzelmann, Gross, et al., 2009; Gunzelmann, Moore, et al., 2009). The ACT-R model can also account for response delays caused by cognitive distraction, since its cognitive capacity constraints allow only one perceptual-motor action to be executed at a time (Salvucci, 2002, 2006). In contrast to the ACT-R model presented by Salvucci (2006), the models in Paper 4 seek to capture the response delays from a vast range of cognitive

states in a single parameter. Thus, the resulting model is simpler, but perhaps somewhat less cognitively accurate, than the ACT-R.

In addition to presenting extensions of the braking model, Paper 4 demonstrates, for the first time, an efficient method to estimate the parameters of a cognitive driver model using data from real-world crashes and near-crashes. Naturalistic data has previously only been used to set the parameters of cognitive models for routine, non-critical, driving (Gordon & Srinivasan, 2014). Using real-life driving data is much more challenging than using data collected from controlled experiments, particularly because of their vast variability (see Section 3.1). Although the manually tuned model presented in Paper 3 could also qualitatively reproduce observations in naturalistic driving data, the solid parameterization in Paper 4 was necessary to ensure model representativeness and capture the influence of off-road glances.

Paper 4 demonstrates that models with parameters which were estimated on less critical data (near-crashes) could accurately reproduce driver responses in situations of higher criticality (crashes). For the brake initiation and modulation models in Paper 4, no differences in fit were observed when the models were parameterized using a data set with only crash data and when then were fit to data sets containing both crash and near-crash data (even with a near-crash/crash ratio of four). These findings indicate that it is possible, at least for some conflict scenarios, to use near-crash data instead of crash data to parameterize a critical event response model. However, it still needs to be determined to what extent this finding is generalizable to other data sources, scenario kinematics, and model structures. Nonetheless, much can be gained if it is possible to use non-critical data to construct critical event response models (see, e.g., Guo et al., 2010). The research community as a whole still needs to agree on the validity and potential consequences of using (behavioral and kinematic) data collected in less critical situations, such as near-crashes or other crash-relevant events, as surrogates for crash data. On the one hand, studies have identified clear discrepancies between crashes and near-crashes caused by selection bias and crash heterogeneity (Dingus et al., 2016; Jonasson & Rootzén, 2014; Knipling, 2015, 2017). On the other hand, pre-evasive kinematics have been shown to be similar between crashes and near-crashes, at least in specific scenarios (e.g., rear-end; Bärgman, Lisovskaja, et al., 2015; Dozza, 2020; Olleja et al., 2022; T. Victor et al., 2015).

While the ideas behind the driver models built on the predictive processing

framework are relatively simple and intuitive, the resulting driver behavior models are highly complex. The high number of unknown parameters results in a tedious, time-consuming parameter estimation process, which may not be feasible within a reasonable time frame with conventional optimization methods. The first estimate of the time required for a full-grid simulation setup to estimate the parameters of the most complex model in Paper 4 was 40 years (assuming 100,000 central processing unit cores). Simplifications in the model structure may be necessary to make the models applicable in practice. Paper 4 addresses this issue in two ways, by (1) assuming constant values for a subset of the parameters and (2) using a stochastic optimization method (particle swarm optimization; see Section 3.3). Nonetheless, the estimation was still computationally expensive, and it would certainly not have been feasible in real time (in an ADAS, for example). This insight emphasizes the importance of considering the intended driver model application when choosing a modeling framework.

In summary, with the research presented in Papers 3–4, driver response models for critical longitudinal situations have reached maturity. The models are validated on real-world data and thus enable virtual safety benefit assessment for lead vehicle events with the driver model in the loop (e.g., AEB effectiveness evaluations; Seyedi et al., 2021; Sugimoto & Sauer, 2005; X. Yang et al., 2022). The models could also be extended to include responses to warnings (e.g., FCW), to complete the system-driver response chain in simulated critical situations. The possibility of performing simulations with a driver model in the loop enables the prospective safety benefit assessment of conceptual and future ADASs. It also contributes to human-centric and cost-efficient ADAS development, verification, and validation processes. As a consequence, it will be possible for new ADASs to quickly enter the market and contribute to even safer roads. Moreover, warnings and interventions can be tailored to (presumed) driver reactions, improving drivers' ADAS usage rates and acceptance.

## Lane departure recovery by steering

While this thesis has elevated the maturity of computational driver models for braking in critical situations to a level that is useful for industrial applications, much more work remains to reach the same maturity for steering models. Most research in this area has concentrated on modeling drivers' steering control

during routine driving on curved roads (A. Li et al., 2019; Markkula et al., 2018; Salvucci, 2006, 2011), during intentional lane changes (Cheng et al., 2020; Salvucci & Gray, 2004), or during (non-critical) lane keeping (Gordon & Srinivasan, 2014; Markkula et al., 2018; Martínez-García & Gordon, 2017, 2018; Martínez-García et al., 2016; Salvucci & Gray, 2004). A few publications considering critical situations include Salvucci and Gray's paper on the two-point steering model (2004) which served as a basis for the ACT-R steering model described by Salvucci (2006) and the lane-keeping model by Markkula et al. (2018). Furthermore, Goodridge et al. (2022) propose that human steering responses in lane departure situations can be explained by evidence accumulation, but no model was constructed in their work. Nevertheless, their study results indicate that the predictive processing and noisy evidence accumulation framework has great potential for the construction of lane departure response models.

For cognitive plausibility, the quantity guiding the driver's steering response should preferably be perceptually available to the driver. In the longitudinal domain, looming was used since it is the optical equivalent of TTC. However, in the lateral domain, a consensus on a corresponding quantity, or risk metric, to quantify the risk subjectively perceived by the driver cannot be found in the current literature. Hence, Paper 6 investigates a set of suggested lane departure risk metrics guiding the drivers' recovery maneuvers at unintended lane departures on straight roads. Each explored risk metric is based on one of four different entities inspired by the literature: (1) the inverse time to lane crossing (iTLC), a quantity equivalent to inverse TTC in a longitudinal scenario (Boer, 2016; Cheng et al., 2020); (2) the splay angle, the angle created by the optical projection (on the driver's retina) of the driving path and a vertical line (Beall & Loomis, 1996; E. S. Calvert, 1954; L. Li & Chen, 2010; Warren, 1982); (3) the critical yaw rate, the yaw rate required to depart from the road at a precise preview distance (Daniello et al., 2013; Gordon et al., 2010; Gordon & Srinivasan, 2014; Gordon et al., 2009; Martínez-García & Gordon, 2018); and (4) the yaw angle relative to the road heading. (See Paper 6 for a detailed description of each risk metric.) The use of splay angle and relative yaw angle information is attractive since angular information is directly perceivable by the visual system. However, iTLC and critical yaw angle are not as perceptual available.

Research has shown that drivers may use optic flow (or, physically, retinal

flow, the retinal projection of optic flow; Gibson, 1950, 1954) as complementary information to guide steering (Kountouriotis et al., 2016; Lappi, 2013; L. Li & Chen, 2010; Mole et al., 2016; Okafuji et al., 2018). Attempts have been made to mathematically express optic flow information so that it can be applied in computational models (Longuet-Higgins & Prazdny, 1980; Okafuji, 2018). It is, however, difficult to quantify how the driver perceives optic flow without making explicit assumptions about the gaze direction and rotation of the driver's head and torso—assuming, for example, that drivers look where they want to go (Wann & Swapp, 2000; Wilkie & Wann, 2003; Wilkie et al., 2008). However, recent research revealed occurrences of steering corrections during off-road glances (i.e., a direct gaze does not precede the steering action; Nguyen, 2021). It thus remains to be investigated whether drivers use optic flow information captured by the peripheral visual system during off-road glances in the decision to initiate evasive steering (and, more importantly, whether and how this can be modeled). In addition, optic flow information is generally not available in the simulation environments for which the computational driver models discussed in this thesis are intended (at least not to any detailed extent). It may also be challenging to reliably estimate how much optic flow information that accurately represent what is typically available to drivers in real-world critical situations. Based on this reasoning, the potential influence of optic flow was deliberately left out of the study in Paper 6.

Paper 6 used correlation analysis and constructed Bayesian linear regression models based on the proposed lane departure risk metrics. Although the choice of risk metrics was based on the literature, most of the selected metrics were not previously related to corrective maneuvers. However, in a driving simulator study, Hildreth et al. (2000) observed increased corrective steering amplitudes with increased initial heading angles. Even though the number of experiment participants was low (only six drivers), the observations were consistent across all participating drivers. The heading in Hildreth's experiment corresponds to the relative yaw angle described in Paper 5, which found a similar relation between this angle and the steering amplitude.

Overall, models based on the relative yaw angle showed great potential in modeling the amplitude of the primary steering correction during an unintended lane departure, outperforming models based on more complex metrics. Nonetheless, the change in splay error turned out to be a more suitable risk

metric when analyzing lane departures extracted from naturalistic data sets (excluding driving simulator data). This difference in relevance may be explained by the different event severity levels for the lane departures in the naturalistic data sets and in the simulator data set; alternatively, behavioral differences between the artificial, heavily controlled simulator setup and an actual vehicle on a real road may be the cause (see, e.g., Engen, 2008, for an overview of how driving in a simulator may differ from naturalistic driving). More research is needed to understand which risk metric (or combination of risk metrics) would be most suitable for which situation.

To the author's best knowledge, the way that the three data sets with different characteristics were combined for most of the analyses in Paper 6 has not previously been reported in the driver modeling literature. Although all data sets contained unintended lane departures, the criticalities of the departures were different. Moreover, the data collection and analysis methods differed somewhat between the data sets. Whereas the fusion of several data sources may contribute to the generalizability of the results, it also raises questions about the comparability of the data sets and, thus, the validity of the analysis results. It was, however, possible to fit a single steering amplitude model to the combination of data sets, although a separate analysis showed that it may be preferable to use different risk metrics for the simulated and naturalistic data sets. Thus, despite the additional noise induced by the data set differences, the main conclusions regarding glance response times hold for all three data sets. Hence, the results can be considered more robust and generalizable than would have been the case had only a single homogeneous data set been analyzed.

The lane departure risk metrics identified in Paper 6 can be used as the perceptual basis for future corrective steering models intended to describe driver control in critical lane departure situations. The construction of these models is a prerequisite for virtual evaluation of LKSs with a virtual driver in the loop. Adding a driver model to the ADAS effectiveness evaluations contributes to improved safety estimates, particularly if the virtual driver can also respond to warnings and automatic interventions. Thus, corrective steering models have the potential to improve the development, verification, and validation process of ADASs for lateral critical situations. In the long term, this may lead to a fewer unintentional lane departures and lost lives.

## 5.3 Glance behavior in driver models

Although inappropriate glance behavior (in particular, off-road glances that are ill-timed, extended, or frequent) is associated with increased crash risk (Dingus et al., 2016; Horrey & Wickens, 2007; S. Klauer et al., 2006; T. Victor et al., 2015), few computational driver models consider how off-road glances impact drivers' decision making and control behaviors. As a result, simulated drivers are, for practical applications, always assumed to either direct their gaze toward the forward roadway or not take any visual input into account at all during off-road glances (essentially assuming they are "blind" at these occasions; Bärgman, Lisovskaja, et al., 2015; Bärgman et al., 2022; Michaud, 2018; H. H. Yang & Peng, 2010). Despite the numerous publications describing drivers' ability to perform actions without looking at the road (Cooper et al., 2013; Hildreth et al., 2000; Lehtonen et al., 2018; Summala et al., 1996), the use of peripheral vision is typically overlooked in computational driver models.

Paper 4 demonstrates how gaze direction can successfully be considered in a critical event response model. By adding a scaling parameter to the input signal, the simulated driver can perceive parts of the looming input during off-road glances, presumably through the peripheral visual system. It was estimated that drivers processed, on average, 30–40 % of the actual looming input when they looked away from the road ahead. The low sensitivity to looming resulted in delayed braking responses for visually distracted drivers. Whereas researchers have not reached a consensus on whether the retinal periphery is less able to process looming or detect collisions than the fovea (N. G. Kim, 2013; F. X. Li & Laurent, 2001; Stoffregen & Riccio, 1990), the results in Paper 4 indicate that human drivers are less sensitive to perceptual input when it is captured by the peripheral visual system. This finding is consistent with the results from several studies on peripheral collision detection in both simulated and real vehicle settings, which show that the timing of a driver's braking response is correlated to the gaze direction (i.e., visual eccentricity with respect to the threat ahead; Burns et al., 2000; Lamble et al., 1999; Summala et al., 1998).

A decreased sensitivity to perceptual input also aligns with the findings from the driving simulator experiment presented in Paper 5, which investigated the relation between glance and brake response times in critical lead vehicle scenarios. The results showed delayed brake responses for the drivers that, during

the critical event, performed a distraction task positioned at high eccentricity, while the glance response times were unaffected by the visual eccentricity level (at least for the subset of drivers who successfully detected the approaching lead vehicle). However, the threat detection rate was decreased at high eccentricities ($> 40°$), in line with the scarce previous literature on the topic (Burns et al., 2000; S. Yang et al., 2022). The poor detection rates can potentially be related to the visual field capabilities of the study participants, since the highest investigated eccentricity corresponded to the limits of the lowest legally required visual field for European drivers (European Parliament, 2006). Since evidence suggest that peripheral visual field loss is associated with decreased threat detection rates and braking response times (at least in the absence of effective compensation strategies; Lockhart et al., 2009; Patterson et al., 2019), measuring the useful field of view of each participant was considered in the preparations for Paper 4. Although these measurements were never effectuated, they could have shed light on whether (and how) varying visual field capabilities influenced the drivers' ability to detect the peripheral threat (i.e., the decelerating lead vehicle) in Paper 6. Deeper insights into how the visual field size impacts the threat detection abilities of individual drivers could be gained by measuring participants' visual field in future studies.

The results in Paper 5 demonstrate that drivers are capable of peripheral threat detection, and that perceptual input processed by the peripheral visual system may be used to guide drivers' gaze directions (i.e., make a distracted driver look back towards the forward roadway). It further extends the conclusions from a study performed by Lamble and colleagues (Lamble et al., 1999; Summala et al., 1998) to unexpected and critical scenarios. Lamble et al. (1999) used a forced peripheral vision paradigm to study brake reaction times to a slowly decelerating lead vehicle. Their study participants were instructed to constantly keep their gaze on a distraction task (even when braking). Similar to the observations presented in Paper 5, a strong inverse correlation was established between TTC at brake initiation and task eccentricity.

In the study presented in Paper 5, the motor response (braking) always followed the redirection of the gaze. Thus, similarly to what was suggested by Engström (2010) and Ljung Aust et al. (2013), drivers do not respond until the criticality of the situation has been assessed. That is, drivers look back on the forward roadway before responding to a critical event in front. This observation does, however, not seem to generalize to the lateral domain. Paper 6

suggests that initiating evasive steering in response to an unintended lane departure is possible while looking off-road. This finding is in line with the results from a study by Summala et al. (1996), in which experienced drivers managed routine lane keeping without looking at the road. Inexperienced drivers were less successful but their performance improved with practice. Drivers' ability to initiate steering during off-road glances, as demonstrated in Paper 6, constitutes yet another piece of evidence for the use of peripheral vision in threat detection and decision-making during critical driving situations. Furthermore, the observed differences in perceptual-motor response between the lateral and longitudinal domain (i.e., that gaze leads motor response in longitudinal, but not necessarily in lateral, situations) indicate that the decision to brake as a result of an already-detected threat is based mainly on visual input in the foveal area, while steering may be guided more by peripheral cues. More research is necessary to confirm this claim, since it partly contradicts previous observations from an experiment in which the participants were instructed to run and stop at a target, decreasing their speed at the last possible moment (Bardy & Laurent, 1989). The study reported that restrictions in peripheral vision led to longer stopping distances, which supported the authors' hypothesis that peripheral cues are used to estimate time to collision (and thus, when to initiate braking).

The results in this thesis demonstrate the importance of considering gaze direction in computational critical event response models: drivers may both acquire perceptual input (to various degrees) and perform control actions during off-road glances. However, gaze direction is not necessarily equal to attention direction (see, e.g., Kujala & Lappi, 2021, for a discussion on how attention may relate to uncertainty and how the processing of uncertainty can be modeled in a predictive processing framework). In fact, many drivers look in the direction of a threat without reacting, with an accident as the result (this is commonly called "looked but failed to see"-crashes, see, e.g., the review by I. D. Brown, 2005). This behavior could be explained by false driver expectations (the role of driver expectations is discussed in Papers 3 and 4), but also by two psychological phenomena: change blindness and inattentional blindness. Change blindness is the failure to notice scene changes that are very easily spotted once identified (Rensink et al., 1997; Simons & Rensink, 2005). It may be caused by interfering visual stimuli or eye movements (blinks and saccades). Inattentional blindness, which is related to expectations, is the

inability to detect the appearance of a new object in the scene when the attention is engaged in something else (Mack & Rock, 1998).

The effects of change blindness and inattentional blindness are difficult to incorporate explicitly into a computational driver model, although integrating them into a high-level prediction layer (Engström, Bärgman, et al., 2018; see also Paper 3) might be a feasible alternative. In Paper 4, the prediction error gain was scaled to reflect the driver's cognitive state, which may also capture some of the effects of change or inattentional blindness. Further research is needed to understand in detail how similar mechanisms could best be reflected in a driver model. Since "look but failed to see" is a relatively common crash causation factor in critical situations that involve vulnerable road users or motorcycles, this understanding is of particular importance for driver models intended for such situations (Clabaux et al., 2012; Herslund & Jørgensen, 2003; Koustanaï et al., 2008). Moreover, it is essential to consider these phenomena when analyzing real-world crashes to find mechanisms that can form the basis of driver behavior models.

Improved understanding of drivers' gaze behaviors in critical situations—and how these behaviors relate to visual attention—can not only contribute to the construction of accurate driver response models but may also facilitate in-depth crash investigations (Islam & Kanitpong, 2008; Sandin & Ljung, 2007). Moreover, such knowledge can be valuable input for the design of more efficient ADASs can be designed (distraction warning systems, in particular; Doecke et al., 2020).

## 5.4 Cognitive model applicability for ADAS tuning

While it should again be emphasized that the choice of computational framework should be adapted to the intended model application, some models may be used in several application areas. Models based on concepts from cognitive science and neuroscience have a solid theoretical foundation. This base enables realistic simulations of the perception-action processes involved in driving and improves the analysis of the cognitive processes behind motor actions (Salvucci, 2006). In addition, the models are often intuitive and easy to analyze. Since the cognitive models presented in this thesis are intended for offline use, they do not require computationally efficient parameter estimation methods that enforce specific model structures (such as the PrARX

structure).

Cognitive driver models, which only rarely exhibit the characteristics of easily parameterized models, are not often used for online ADAS tuning. A natural step toward making online driver models more psychologically plausible would be the exclusive use of visually perceivable entities, such as looming, as model input. However, the model structure may still not be cognitively accurate.

An alternative to enforcing cognitive structures in online models is to use the cognitive models to tune ADASs (offline) during system development. This approach would lead to an initial tuning that is optimal on a group level. The default parameters can later be fine-tuned to individual drivers in real time by using model structures similar to those in the hybrid ARX framework. Similar methods are typically applied to train ML-based driver models on large sets of driving data. Pre-tuned models can subsequently be integrated into personalized ADASs or AD systems (see e.g., Lu et al., 2018; Zhao et al., 2022; Zhu et al., 2018).

## 5.5 Limitations and future work

One of the main limitations of driving behavior studies, particularly for those targeting critical situations, is the lack of appropriate data. Fortunately, accidents are rare events, and recorded real-world accidents are even more scarce. The vast situational and behavioral variability among drivers adds to the challenge of finding sufficient data.

Another limitation related to the collected and analyzed data is the lack of generalizability of driver behaviors, and thus of the driver models, to other geocultural areas. Most data used for the work in this thesis were collected on European or US roads or in simulated environments with similar characteristics. More research is needed to understand how the models can be adapted to different populations and driving environments.

The computational driver models presented in this thesis need further validation on more extensive data sets. The general conclusions drawn about driver behaviors should be confirmed by, for example, replicating the studies. Fortunately, because of the generalizability of the proposed modeling frameworks, they can be used to construct models intended for other traffic situations as well, such as critical intersection scenarios. In particular, models

for the lateral driving domain can be improved by using the lane departure risk metrics identified in Paper 6 as input to a noisy evidence accumulation model combined with the predictive processing framework. In fact, Engström et al. (2022) discuss how a framework very similar to the one used in Papers 3–4 can be generalized to any traffic scenario. However, their work uses a surprise concept instead of the prediction error in the accumulation process. The authors demonstrate how the surprise can be calculated using a generative statistical model.

As the level of vehicle automation increases, many ADASs are becoming standard in new cars. Future driver models must be able to adapt to the corresponding, inevitable effects on driving. As previously mentioned, some advancements have already been made in this area, by using the predictive processing framework to model delayed brake responses when drivers are exposed to silent failures of an ACC system (Bianchi Piccinini et al., 2020). Similar models could be constructed for other ADASs, and potentially for the hand-over phase of SAE level 3 (SAE International, 2021) automated driving systems (i.e., systems requiring a fallback-ready user but not constant supervision). It might also be beneficial to include how ADASs influence the drivers' behaviors in the driver models indended for multi-agent microscopic traffic simulations: in this way, the effects of mixed traffic with different proportions of manually driven, semi-automated, and fully automated vehicles could be evaluated (S. C. Calvert et al., 2020; Farah et al., 2022). In addition, effects of driver variability, driver errors, and driver distraction could be added to the microscopic traffic simulation models to make them more realistic (Fries & Fahrenkrog, 2021; Fries et al., 2022; van Lint & Calvert, 2018). However, the validity of multi-agent microscopic traffic simulations, for safety benefit assessments, still remains an open question.

Given the relatively low maturity of models targeting lateral control in critical situations, another exciting area of future research is the combination of perception-based and neuromuscular steering models (e.g., the neuromuscular model suggested by Benderius, 2014). A perceptual-neuromuscular steering model would simulate of a detailed, realistic, steering maneuver, including both reflexive and conscious behaviors. The perceptual part could determine the steering adjustment's timing and amplitude, while the neuromuscular part would guide the exact execution of the steering adjustments (i.e., determine the shape of the steering signal during the adjustments).

Similarly, computational driver behavior models targeting the pre-crash phase may be combined with biomechanical active human body models (D. Kato et al., 2018; Larsson et al., 2019; Östh, 2014). This way, a comprehensive virtual toolchain for integrated safety (Wågström et al., 2019) can be constructed. This toolchain would be able to assess both crash and injury risk for the driver and passengers in critical traffic situations. Recent advances have been made in finite-element simulations of driver posture (Leledakis, Östh, et al., 2021; Östh et al., 2014) and muscle activation in pre-crash situations (Östh et al., 2015, 2022). However, more research is needed to understand how best to conduct comprehensive assessments of crash and injury risks.

Finally, further research is needed regarding which data should be used as a basis for computational driver models. Even though recent initiatives are collecting vast amounts of data in naturalistic settings, resulting in huge data sets such as the SHRP2, the number of critical events is still not sufficient for model building. Moreover, studies have pointed out that using near-crashes (which are generally available in larger numbers than crashes) as surrogates for crashes has some drawbacks: the practice may result in underestimation of the crash risk (Guo et al., 2010), may not give a reliable crash severity estimation (Tarko, 2018; Zheng et al., 2014), and may not yield representative impact speed distributions (Olleja et al., 2022). Hence, further research is necessary to understand the relationship between crashes, near-crashes, and other crash-relevant events, in order to know to what extent less-critical data can be used to model and parameterize critical event response models. It is reasonable to believe that there will be no general conclusion valid for all kinds of situations; thus, investigations must be done separately for each type of critical event.

Another problem with most naturalistic driving databases is that much of the necessary data, such as kinematic data describing the movement of surrounding road users, are still lacking. With the possibilities emerging from wireless data transfer and cloud storage, large fleet databases collected by vehicle manufacturers or other commercial actors (see, e.g., Carney et al., 2015) should to become increasingly common in the future. Commercially collected NDD (Bärgman, Lisovskaja, et al., 2015) have the potential to provide enormous quantities of driving data—but efficient data mining methods will be needed to identify and extract driving sequences that are suitable for the construction or parameterization of computational driver models.

# CHAPTER 6

# Conclusions

This thesis investigated how computational driver models can be constructed and used in the ADAS development chain from the concept phase to the last stages of verification and validation—and even as part of the final product. Methodological advances contributing to our understanding of how human control behavior can be translated into mathematical models were made in the construction and practical application of driver models, for both longitudinal and lateral control.

In both control domains, steps were taken toward real-time ADAS adaptation by enabling continuous, online identification of driving styles. Furthermore, the work in this thesis contributed to improved methods for simulation-based safety evaluations by suggesting validated kinematics-dependent models of human braking behavior, parameterized using real-world crash and near-crash data. The benefit of expressly including gaze direction information in the models was also demonstrated. Initial steps were also taken to create similarly valid models in the lateral domain, describing recovery maneuvers during unintended lane departures.

The main conclusions related to the research questions formulated in Section 1.1 are summarized as follows:

*1. How can driver behavior be estimated in real-time to enable online tuning of ADASs?*

This thesis showed that real-time prediction and classification of drivers' style and braking intent could be accomplished using PrARX models, which have a model structure facilitating online parameter estimation (Paper 1; *RQ 1.1*). However, since such complex model structures cannot be justified when performing behavior prediction over more than one time step, classification models could be considered a better alternative for continuously tuning ADASs to the individual driver (Paper 2; *RQ 1.2*).

*2. How can driver behavior in critical situations be computationally modeled?*

The predictive processing and noisy evidence accumulation framework can construct psychologically plausible human brake response models. The framework enables the development of kinematics-dependent driver models that can qualitatively reproduce driver behaviors found in real-world crashes and near-crashes. The generic predictive processing and evidence accumulation principles can also be applied when modeling other types of driving behavior, using perceptual quantities suitable for the targeted scenarios. (Papers 3–4; *RQ 2.1*)

In the lateral domain, relative yaw angle and change in splay error were identified as promising risk metrics for lane departure recovery maneuvers. These metrics can be included in the design of cognitively-based steering amplitude models. (Paper 6; *RQ 2.2*)

*3. How does the gaze direction influence the driver's behavior in critical situations?*

Expressly considering gaze direction and scaling the perceptual input accordingly improve driver model performance (Paper 4; *RQ 3.1*). Further improvements could be achieved by considering the exact gaze angle, since increasing gaze angles are associated with increasing brake response times in critical

lead vehicle scenarios (Paper 5; *RQ 3.2*). Interestingly, and surprisingly, the corresponding glance response times seem unaffected by visual eccentricity.

The above findings, together with the observation that drivers can initiate evasive steering to avoid lane departures without first looking on-road, demonstrate the importance of considering peripheral vision in driving. (Papers 4–6; *RQ 3.3*)

In addition to contributing to a deeper understanding of how to model human cognition and control in driving, the methods and models demonstrated in this thesis will ultimately be a part of more human-centric and cost-efficient ADAS development, verification, and validation processes, as well as warning and intervention systems adapted to each individual driver. Specifically, cognitive driver models enable offline virtual safety evaluations with the driver in the loop, whereas real-time, data driven models have the potential to improve ADAS usage. These advances will result in safer cars, thus playing an important role in the fulfillment of the United Nation's sustainable development goals (United Nations, 2015; targets 3.6 and 11.2) by improving safety and reducing the number of fatalities and injuries on the roads.

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