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Driver performance models as reference for the quality of automated driving functions

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Content

Management summary

One main goal in the development of automated driving (AD) functions has always been an improved safety for all road users (BMVI, 2017). With first Level 3 functions available in series-production vehicles and higher automation levels being tested on the road in defined Operational Design Domains (ODD), the challenge remains for developers to argue the level of safety of the specific function. Different approaches have been defined to technically achieve this challenge, with one critical aspect being the answer to the question: *How safe is safe enough*?

The focus of this report is on reviewing driver performance models used as reference for AD functions. The primary benefit of using a driver model as a reference is that it establishes a human-centric benchmark against which AD functions can be evaluated. By basing this benchmark on human driver performance, it becomes possible to assess how well automated systems align with or exceed human driving and performance capabilities.

To this end, literature on human driving performance was reviewed as a basis for (the interpretation of) reference model specification and validation. Human driving performance is inherently complex and multifaceted. Depending on the specific use case, different aspects of human performance should be in the focus of driver models. Among the most critical components are visual perception and the driver's response to (visual) input. Additional relevant factors include the driver's state, such as impairments like fatigue or drowsiness. Following from this, one central argument for each reference argumentation on performance concerns the characteristics of the defined reference population or reference driver(s) that shall be represented by the model output.

Varieties of driver models exist that each claim to capture driving performance and provide a reference for AD functions. In this report, an overview over existing models is given and analysis criteria are introduced to make different models comparable. The reviewed model types include reaction-based models, which are the most prevalent and have even been incorporated into regulations. These models typically include fixed response times for human reactions to predefined stimuli in challenging driving scenarios, along with the corresponding reaction strength. More advanced models account for variable stimuli and argue responses based on concepts such as the human drivers' surprise. Such models also aim to emulate the performance of a competent and cautious driver, setting a higher benchmark than the average human driver.

Other models focus on providing benchmarks for tactical decisions, such as performing a lane change. Simpler rule-based models define a safety envelope for automated vehicles and have been used as reference points. At the more complex end of the spectrum are cognitive models. These aim to replicate the entire cognitive process of human drivers, including perception, decision-making, and motor control. Cognitive models are particularly valuable for simulating human driver errors, making them essential tools for concepts like the Positive Risk Balance

(PRB) of automated driving functions. These models generally aim to reflect the distribution of human performance across the general population of drivers.

Despite their utility, most of the driver models analyzed in this report lack thorough validation or sometimes even basic plausibility checks. A key prerequisite for improving model reliability is the availability of adequate performance data. Different types of data collection methods are required to cover normal, challenging, and accident scenarios, each presenting unique challenges. Available solutions for data generation include naturalistic driving studies, observing naturalistic traffic with drones or infrastructure-based equipment and, especially for challenging scenarios, creating customizable environments on test tracks or in driving simulators to collect human performance data. Examples from literature for the parametrization of models and the comparison of performance output with different data sources are provided in this report. To advance the field, we propose the creation of a unified comparison of the performance boundaries of different reference models in a selection of relevant driving scenarios, as well as the comparison to different data sets to allow for plausibility checks of the different models against the data.

Ein Hauptziel bei der Entwicklung von Funktionen für das automatisierte Fahren war stets eine verbesserte Sicherheit für alle Verkehrsteilnehmer (BMVI, 2017). Mit den ersten Level-3-Funktionen, die in Serienfahrzeugen verfügbar sind, und höheren Automatisierungsstufen, die in definierten Betriebsbereichen auf der Straße getestet werden, bleibt für Entwickler die Herausforderung bestehen, das Sicherheitsniveau der spezifischen Funktion nachzuweisen. Verschiedene Ansätze wurden definiert, um diese Herausforderung technisch zu bewältigen, wobei ein kritischer Aspekt die Beantwortung der Frage „Wie sicher ist sicher genug?“ ist.

Der Schwerpunkt dieses Projektberichts liegt auf einer Übersicht von Fahrermodellen, die als Referenz für Funktionen des automatisierten Fahrens verwendet werden. Ein zentraler Vorteil der Verwendung eines Fahrermodells als Referenz besteht darin, dass es einen menschzentrierten Maßstab schafft, an dem das Verhalten automatisierter Fahrfunktionen bewertet werden kann. Durch die Nutzung von Referenzmodellen ist es möglich zu beurteilen, wie gut automatisierte Systeme mit der Leistung (bestimmter) menschlicher Fahrer(-populationen) übereinstimmen oder diese übertreffen.

Vor dem Hintergrund menschlicher Leistung als Grundlage der Referenzbeurteilung wurde im Projekt zunächst Literatur zur menschlichen Fahrleistung analysiert, um eine Basis für (die Beurteilung der) Spezifikation und Validierung von Referenzmodellen zu schaffen. Die menschliche Fahrleistung ist von Natur aus komplex und vielschichtig. Abhängig vom spezifischen Anwendungsfall stehen unterschiedliche Aspekte der menschlichen Leistung im Fokus der jeweiligen Fahrermodelle. Zu den kritischsten Aspekten menschlicher Leistung gehören die visuelle Wahrnehmung und die Reaktion des Fahrers auf (visuelle) Reize. Weitere relevante Faktoren umfassen den Fahrerzustand, wie Beeinträchtigungen durch Müdigkeit oder Schläfrigkeit. Ein zentrales Argument für jede Referenzargumentation zur Leistung betrifft daher auch die Eigenschaften der definierten Referenzpopulation oder des Referenzfahrers, die durch die Modellierung dargestellt werden sollen.

Es existieren verschiedene Fahrermodelle, um die Fahrerleistung abzubilden und eine Referenz für Funktionen des automatisierten Fahrens bereitzustellen. In diesem Bericht wird ein Überblick über bestehende Modelle gegeben und es werden Analysekriterien eingeführt, um die Vergleichbarkeit verschiedener Modelle zu ermöglichen. Das Spektrum umfasst einerseits reaktionsbasierte Modelle, die am weitesten verbreitet sind und teils bereits in Zulassungsregularien integriert wurden. Diese Modelle beinhalten typischerweise feste Reaktionszeiten für menschliche Reaktionen auf vordefinierte Reize in kritischen Fahrszenarien sowie die entsprechende Reaktionsstärke. Fortschrittlichere Modelle berücksichtigen variable Reize, z.B. basierend auf der Erwartungshaltung des menschlichen Fahrers. Einige dieser Modelle zielen zudem darauf ab, die Leistung eines kompetenten und vorsichtigen Fahrers zu emulieren, wodurch ein anspruchsvollerer Maßstab als der eines durchschnittlichen menschlichen Fahrers gesetzt wird.

Andere Fahrermodelle konzentrieren sich darauf, taktische Entscheidungen wie Spurwechsel abzubilden. Einfache regelbasierte Modelle definieren eine Sicherheitskriterium für automatisierte Fahrzeuge und wurden als Referenzpunkte verwendet. Am komplexeren Ende des Spektrums stehen kognitive Modelle. Diese zielen darauf ab, den gesamten kognitiven Prozess menschlicher Fahrer nachzubilden, einschließlich Wahrnehmung, Entscheidungsfindung und motorischer Steuerung. Kognitive Modelle sind besonders wertvoll, um menschliche Fahrfehler zu simulieren, und bilden beispielsweise die Basis zur Ableitung der sog. positiven Risikobilanz (Positive Risk Balance, PRB) von Funktionen des automatisierten Fahrens. Diese Modelle streben im Allgemeinen an, die Verteilung der menschlichen Leistung über die gesamte Fahrerpopulation hinweg zu reflektieren.

Trotz ihres Nutzens mangelt es den meisten in diesem Bericht analysierten Fahrermodellen an einer gründlichen Validierung oder teils sogar an grundlegender Plausibilisierung. Eine zentrale Voraussetzung zur Verbesserung der Modellzuverlässigkeit ist die Verfügbarkeit geeigneter menschlicher Leistungsdaten. Grundsätzlich sind verschiedene Erhebungsmethoden geeignet, um normale bis hin zu herausfordernden Szenarien oder gar Unfälle abzudecken. Verfügbare Lösungen zur Datengenerierung umfassen naturalistische Fahrstudien, die Beobachtung realer Verkehrssituationen mit Drohnen oder infrastrukturbasierten Erhebungsstationen und, insbesondere für herausfordernde Szenarien, die Erstellung maßgeschneiderter Umgebungen auf Teststrecken und in Fahrsimulatoren, um Leistungsdaten von Fahrern zu sammeln. Beispiele aus der Literatur zur Parametrisierung von Modellen und zum Vergleich von Fahrerleistungsverteilungen auf Basis verschiedener Datenquellen werden in diesem Bericht bereitgestellt. Um das Forschungsfeld voranzubringen, schlagen wir die Erstellung eines einheitlichen Vergleichs der Leistungsgrenzen verschiedener Referenzmodelle in einer Auswahl relevanter Fahrszenarien vor, sowie den Vergleich mit unterschiedlichen Datensätzen, um eine Plausibilisierung der verschiedenen Modelle gegenüber den Daten zu ermöglichen.

1 Introduction

"The primary purpose of partly and fully automated transport systems is to improve safety for all road users." (BMVI, 2017)

While automated driving (AD) systems promise to reduce traffic incidents caused by human error (Martinez-Diaz & Soriguera, 2018), an important challenge still remaining is the definition of the level of safety reached by an AD function. Mattas et al. (2022) defines multiple possible approaches to address this issue. These include setting a general safety target, a safety target over a fixed number of traffic scenarios, operational requirements for the AD function, or a performance target for a set of traffic scenarios. The latter approach has the benefit of setting clear vehicle design targets and can be easily assessed (Mattas et al., 2022).

A natural performance target to choose is the human driver, since a key safety requirement of the AD function is the diminution of harm when compared to human drivers (BMVI, 2017). To translate the performance target into practice, driver performance models can be used as a reference for the AD function. Driver models allow for easy evaluation of the human performance in simulation. This concept has also been proposed in regulation (UNECE, 2021) and research projects as part of a wider validation and verification methodology for AD functions (Bachorek et al., 2024).

In this report we provide a detailed overview of human driving performance and driver models that capture human driving performance, especially those that are explicitly used as a reference for the safety assessment of automated driving systems, also called driver reference models or reference models. We will further discuss challenges related to the use of such models, especially those posed by the availability of data for the development and validation of these models.

The report starts by introducing the concept of driver models and discussing their applications in the automotive industry. It then explores the motivation for using driver models as a reference. Finally, various applications for reference models are discussed and the concept of risk in the context of safety assessment is introduced. Chapter 2 provides an overview of human driving performance as defined in the literature, focusing on behavior in normal and critical driving, methods for capturing driving performance, and factors influencing driving performance. Chapter 3 presents different approaches to using driver models as a reference for the safety assessment of automated driving systems found in the literature. Chapter 4 discusses available data sources needed for the development of reference models and touches on the validation of these models using the data sources. Finally, Chapter 5 presents the research gaps identified based on the literature reviewed and discusses potential future research directions.

1.1 Driver model applications

A driver model in general is a computational representation of human driving behavior, with the goal of simulating this behavior realistically in a traffic environment. Siebke et al. (2022)

identify two distinct types of driver models: *Predictive models* and *cognitive model*. Predictive models are focused on the reproduction of the behavior themselves, while cognitive models are focused on reproducing the underlying cognitive processes that lead to the behavior (Siebke et al., 2022).

Furthermore, Siebke et al. (2022) make a distinction in application for normal traffic and critical traffic situations. Here, the authors identify different model types that are suited for different applications. For normal traffic situations, the authors suggest the use of *car-following models*, *lane-change models*, and *traffic infrastructure node models*. For challenging traffic situations, the authors mention *reaction time models*, *perception models* and *cognitive models* as suitable model types, with each of the models covering different aspects of the driving behavior. Many of these models will be detailed in Chapter 3, when we discuss the use of these models as a reference for AD functions.

Different models are widely applied in automotive research and design, encompassing several key areas. Some of the most common key areas have been compiled in literature by Levermore et al. (2014). The authors identify the following key areas of application for driver models:

- *Safety*: Driver models help to analyze behavior and detect impairments such as fatigue, distraction, or intoxication, enabling safety measures like fatigue detection or adaptive cruise control (ACC) systems. These models also predict driver interactions with automated systems, aiding in safer integration.
- *Automated Driving*: Driver models predict vehicle behavior in the vicinity to avoid collisions, integrating human-like decision-making into automated systems for smoother coexistence with human drivers.
- *Fuel Consumption*: Simulations incorporating driver deviations (e.g., reaction time) help to evaluate the impact of behavior on fuel consumption and emissions during both regulatory cycles and real-world driving.
- *Driving Style*: Driver behavior research categorizes styles (e.g., calm, normal, aggressive) based on metrics like acceleration and jerk, analyzing their influence on traffic flow, accident rates, and emissions.
- *Traffic Management:* Driver models are crucial for simulating road network scenarios, helping planners to optimize traffic flow and infrastructure changes. Foundational equations predict vehicle acceleration in response to traffic conditions, considering driver-specific characteristics.
- *Vehicle Design:* Driver models influence ergonomic and psychological aspects of vehicle design, particularly with evolving driver aids, ensuring compatibility with driver needs and behavior.

The focus of this report is on the application of driver models in the context of safety. Specifically, we will discuss the use of driver models as a reference for the safety assessment of automated driving systems.

1.2 Scenario-based testing

Automated vehicles must independently perform all levels of the driving task, requiring a complex interplay of various systems. This complexity makes the evaluation of safety of such systems a challenging task. Nonetheless, safety assessment is a crucial prerequisite for the deployment of automated vehicles on public roads.

To ensure safety, automated vehicles must demonstrate reliability across all reasonably expected driving situations in the target Operational Design Domain (ODD). A naive approach would involve extensive road testing; however, this method is impractical due to the immense amount of driving required to encounter rare, safety-critical scenarios in normal driving conditions (Kalra & Paddock, 2016).

A more feasible solution is scenario-based testing, where challenging situations are formalized using data from real-world traffic or expert knowledge. These scenarios can then be tested safely and efficiently in driving simulations, even during the early stages of automated vehicle development, to ensure that functionality was implemented correctly and to provoke possible failures in the AD function (Pütz et al., 2017; Hauer et al., 2019).

A scenario is a sequence of scenes that describe an environment at various points in time (Ulbrich et al., 2015). Additionally, scenarios may include actions, events, conditions, or goals that influence the temporal development of these scenes. Defining a scenario facilitates a structured and deterministic representation of subjective situations that a driver or AD function might encounter. The outcome of a scenario is not predetermined but instead depends on the interactions of various actors involved.

Scenarios can be categorized based on their level of abstraction into functional, logical, and concrete types. *Functional scenarios* are the most abstract, providing a natural language description of events and conditions. They become more specific in *logical scenarios*, which define parameters and parameter ranges for the scenario. For example, a parameter might specify the initial speed of the ego vehicle. At the lowest level of abstraction, *concrete scenarios* assign specific values to these parameters, fully detailing the scenario (Menzel et al., 2019).

Beyond abstraction levels, scenarios also vary in content. One method of classifying scenario content is the six-layer model (Scholtes et al., 2021), which organizes elements into distinct layers:

- *Digital Information (Layer 6)*
- *Environmental Conditions (Layer 5)*
- *Dynamic Objects (Layer 4)*
- *Temporary Modifications of Layers 1 and 2 (Layer 3)*
- *Roadside Structures (Layer 2)*
- *Road Network and Traffic Guidance Objects (Layer 1)*

For a scenario to be usable, such as in traffic simulation, the elements within each layer and their interrelations must be systematically defined. Furthermore, a suitable format is required to represent this content in a way that is comprehensible to the simulation environments and simulation models, including driver models.

1.3 Motivation for reference models

One of the major challenges in safety assessment is selecting the appropriate reference to evaluate safety, essentially asking the question: *How safe is safe enough?*

One way to approach this challenge is to analyze the risk introduced by the AD function and compare against accepted risks (Bachorek et al., 2024). A risk estimation, considering both the severity and probability of concrete scenarios, can be made using the scenario-based testing approach discussed above. To derive the acceptable risk, Bachorek et al. (2024) introduce multiple methods, including comparing to a rule, by being better than a reference or by defining explicit risk values.

One option for such a reference is human performance in the form of reference models (Mattas et al., 2022). Since in current traffic environments, human drivers are among the primary contributors to traffic accidents, it is reasonable to require that automated vehicles behave at least as safe as human drivers. In other words, human performance should serve as the benchmark for assessing the safety of automated vehicles. The benchmark can be utilized to distinguish between avoidable and unavoidable accidents.

This can also be interpreted as a region within the parameter space of the scenario where a collision is deemed unavoidable. The abstract concept for such a region is shown in Figure 1.1. Typically, the reference model so far is designed to represent a specific driver rather than a distribution of drivers. The representative drivers are often selected based on attributes such as being competent, attentive, or skilled.

In this context the concept of Absence of Unreasonable Risk (AUR) is introduced. Unreasonable risks are those that are unacceptable in a society for a certain context (Favaro, 2021). The risk itself is a combination of the probability of harm occurring and the severity of the harm in question. In order for the system to be deemed safe, enough evidence has to be provided to show that no unreasonable risk exists for the system’s application.

An example of a risk assessment using driver models is presented in the PEGASUS Method for Assessment of Highly Automated Driving Function (HAD-F). The method proposes use of the RSS-Model to decide if test cases pass the safety criteria defined in PEGASUS (PEGASUS Project, 2019).

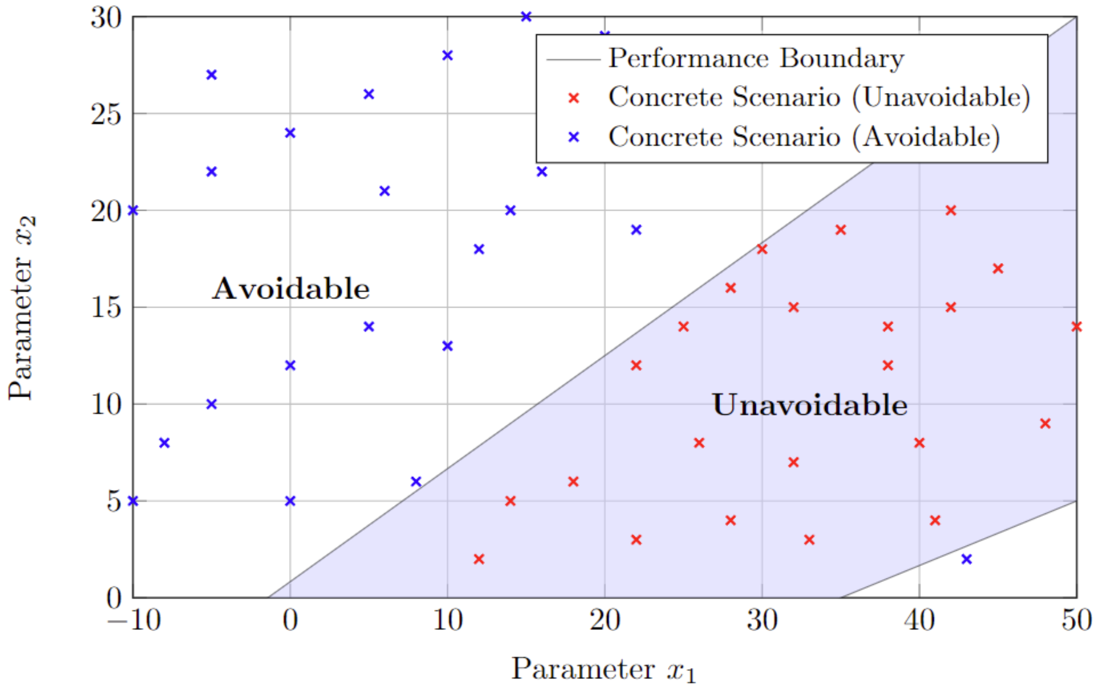

Figure 1.1: Reference model performance boundary

Another possibility is the use of driver models to derive a *Positive Risk Balance (PRB)* as explained in Favaro (2021), Kauffmann et al. (2022) or Fahrenkrog et al. (2023) for the automated driving system. In order to achieve a positive risk balance, it has to be shown that the automated vehicles *"produce at least a diminution in harm compared with human driving"* (BMVI, 2017). In this case, the driver model must represent the entire driver population across all scenarios within the ODD of the automated driving system. Chapter 3 of this report discusses the different approaches in more detail, where different models that are suited to represent a human performance benchmark or models that can be used to derive a positive risk balance are presented.

2 Overview on human driving performance

“Once a motor vehicle begins to move, collision (or veering off the roadway) is not a matter of some refined estimate of a very low probability: it is inevitable. The probability of crashing is one, unless, of course, the driver more-or-less continuously makes direction and speed adjustments to avoid this otherwise certain outcome” (Fuller, 2005, p. 462).

This chapter provides an overview of research and influential theories illustrating how different drivers make adjustments and – in the end – mitigate their collision risk. To consider human driving performance as the reference or benchmark for AD performance, first, an understanding of what constitutes (good) human driving performance is required. The focus of this report is solely on manual driving performance as a reference for AD functions, thereby excluding studies focusing specifically on interactions with driver assistance systems or control transitions from automated to manual driving.

Within this project, literature on human performance when driving a vehicle was aggregated and analyzed from three different foci:

- *existing knowledge about and known influences on human driving performance,*
- *classification of human driving performance,*
- *methods to collect human driving performance.*

Literature for the above-named foci was collected via three different approaches: First, literature already available to the authors was aggregated with a focus on review-papers on driver performance metrics (non-systematic literature review). In addition, references concerning parametrization inputs or human reference aspects from the analyzed human performance models were collected (see overview of analyzed reference models in Chapter 3). Finally, systematic literature research (based on the PRISMA approach; Page et al., 2021) was conducted. The lead questions for the systematic part of literature search were:

- Which (human factors) variables affect driving performance?
- Are there classifications of (human) drivers such as good driver, bad driver, average driver based on driving performance? Based on which characteristics have they been methodically defined?
- Which deficits or limitations of human capabilities regarding vehicle conduction are known?
- How have data (on human performance) been obtained?

Search terms were selected after a first non-systematic review of available publications as a combination of four different topics, i.e., *human driver* AND *characteristic* (characteristic* OR behavior*) AND *performance* (collision avoidance, reaction time* OR hazard perception OR risk perception) AND *use case* (lane AND chang* OR lane AND keep* OR car AND follow* OR classification). The selected use cases were derived from frequent sub-tasks targeted by relevant modelling approaches (e.g., Ahmed et al., 2022; Wang, Guo, Yu, et al., 2024; Engström, Liu, et al., 2024). The initial search of title, abstracts and keywords identified 537 (peer-reviewed) records. Of these, 52 records were selected for full text analysis after exclusion by topic relevance, language (included only: German or English) and data basis. Included in the following analyses after full-text analysis are 52 publications from the systematic literature search in addition to the literature already assembled for the other aspects of this report (e.g. reference models, data sources)[1].

2.1 Driver behavior, performance and driving style

Although the project's focus is on driver performance, analyses included publications on the more general terms *driver behavior* and *driving style* to grasp relevant influences that might be relevant for modeling driver performance as an outcome of individual or different population characteristics. "The concept of driving behavior includes all actions (both overt acts and covert or mental operations) a driver performs during driving. Driving styles are subcategories of driving behavior, satisfying the criteria of varying systematically between individual drivers or groups of drivers and also being habitual" (Sagberg et al., 2015, p. 1252). Driving styles are further thought to reflect choices made by the driver and represent relatively stable behavior (Sagberg et al., 2015).

"Although it is generally assumed that driving styles are related to crash risk, there are still several unresolved issues regarding the details of this relationship and how safe versus unsafe driving styles should best be modeled and measured" (Sagberg et al., 2015, p. 1249). One general finding is that driving styles that are being characterized by abrupt changes in speed and speeding in general have the higher crash involvement (Sagberg et al., 2015). A more detailed review of which characteristics have been used to describe driving styles and which characteristics have been linked to performance indicators and crash risk can be found in Chapter 2.4. Detailed information on how habitual behavior is formed and influenced can be found in the review by Sagberg et al. (2015; see also Wang et al., 2010). The characteristics by which a safe driver might be generally characterized are also subject to (general) human limitations and considered accordingly in this report (see Chapter 2.4).

For reference purposes, especially for scenario-specific considerations of behavior with a focus on conflict handling, we refer to the term *human driver performance* in relation to an outcome, safety- or success-based consideration of behavior, in line with Quante et al., 2021, who state that: "In general, human performance refers to the potential of a person to successfully perform a task". A similar understanding of potential, or capabilities, in relation to demands can be found in the task-capability-model (TCI; Fuller, 2005), as reviewed below. Driver performance in the following chapters is mostly understood in a safety-oriented manner, i.e., the analysis of actions performed (or not performed) with regard to the main goal of driving safely. A short overview is provided on how driving performance is operationalized in the literature (see Chapter 2.3).

[1] The authors would like to thank Doreen Schwarze and Emily Oliveira for their support in conducting the literature research, selection and analysis process.

2.2 From normal driving to crashes

According to the task-capability interface model (TCI; Fuller, 2005), driving performance is defined by the driver's capabilities in relation to the current task demand. The TCI is built around the concept of task difficulty, postulating changes in driving behavior as a means to make the driving task easier. If capabilities exceed task demand, the driver is postulated to be in control of the driving task. The probability of collisions increases if task demand exceeds the driver's capabilities, developing from control to loss of control to collisions (Quante et al., 2021). However, a loss of control does not necessarily lead to a collision, as actions by others or chance ("lucky escape") may still save the driver from a collision. According to Fuller (2005), task demand is "determined by a plethora of interacting elements" (p. 464), amongst others visibility, road signs or operational features of the vehicle. Driver capability is limited by biological characteristics of the driver, including reaction time (understood here as a characteristic of the driver) and information processing capacity (Fuller, 2005). These characteristics are the basis for knowledge and skills ("acquired characteristics"). "Together these biological characteristics and acquired characteristics through training and experience determine the upper limit of competence of the driver" (Fuller, 2005, p. 464). "However, what a driver actually delivers (also referred to as driving performance) often falls short of the optimal capability because of various factors that can impair driving performance." (Saifuzzaman et al., 2015, p. 1). Fuller (2005) explicitly refers to, e.g., motivation, attitude, distraction, emotion, stress and drugs. On the other hand, as also illustrated by the TCI, a collision does not automatically become a certainty if the task demand is higher than the driver's current capabilities. As stated above, this is due to other road users' influence on the situation's development and chance or lucky escapes (Fuller, 2005).

"Demanding situations elicit peak performance capabilities, and routine situations elicit typical (not necessarily best) behavior" (Shinar & Oppenheim, 2011). In routine, normal driving, the exact execution of the driving task offers certain degrees of freedom to the driver, for example in terms of chosen speed or lane choice (in line with the notion of driving as a self-paced task, cf. Fuller, 2005). Drivers' choices during normal driving can influence the probability of demanding situations: For example, a very close following distance does not in itself present a challenge to the driver, so long as the lead vehicle does not perform a sudden braking maneuver, presenting the need to quickly react to a changed situation.

Following Michon's hierarchical framework (Michon, 1985), the driving task can be structured into three different levels: the *strategic level*, e.g. route choice tasks, the *tactical level*, e.g. selecting speed and following distances or making lane change decisions, and the *operational level*, with corrections of deviations from target values by steering and braking input (see also the review by Vollrath & Krems, 2011). The potential challenge introduced above (i.e., sudden braking by a lead vehicle) would not necessarily arise in case of an initially larger following distance, illustrating the driver's potential to influence the probability of challenging scenarios by *tactical decisions*, for example conflict avoidance by choice of adequate safety margins. Next to the drivers' braking or steering reaction in traffic conflicts or during crash mitigation (i.e., the operational level), driver performance can thus also be regarded in terms of adequate tactical behavior.

As Markkula et al. (2012) state for “everyday driving, a driver will routinely pass from a *low risk* state into the *conflict state* […] and then back again to the low risk state as a result of successful use of acceleration, deceleration, steering, or a combination thereof” (p. 1119). However, the (objectively) most effective collision avoidance strategy is not always applied by drivers: “Several researchers have noted a tendency of drivers not to apply steering to the full stability limits of their vehicles and to brake and collide in situations where steering could have avoided the collision” (Markkula et al., 2012, p. 1119). In addition to strategic component in the choice of reactions, “it seems likely that initial steering response is a few tenths of a second faster than initial braking” (Green, 2000, p. 213). Not only the choice of reaction, but also other factors influence the handling success. As Bekiaris et al. (2003) stress, the exact relation between accidents and the preceding behavior is often unclear: “Performance aspects as well as motivational aspects, individual differences and momentary state variables: all of these influences appear to be relevant” (p. 152).

To assess what exactly defines normal driving, Papazikou et al. (2017) analyzed the SHRP2 dataset with the goal to derive indicators representative of baseline, uneventful driving (e.g., TTC, lateral and longitudinal accelerations; see Chapter 2.3). “First of all, an understanding of normal driving is essential in order to effectively detect the onset of hazardous situations so as to prevent crashes” (Papazikou et al., 2017, p. 3). Using post-processed range and relative velocity data from the dataset to calculate the time-to-collision (TTC), the authors identify a threshold value of 4 seconds to provide a 99% confidence level for data to be regarded as normal driving.

Markkula et al. (2012) present and discuss a crash causation model, published by Engström, Victor and Markkula, alongside the four driving conflict states as introduced by Najm and Smith, i.e.: *low risk*, *conflict*, *near-crash* and *crash*. According to the model by Engström, Liu, et al., crashes may be prevented by two barriers, namely the *proactive barrier* between a conflict and a near-crash and the *reactive barrier*, separating a near-crash from a crash. Following the model, the correct schemata, i.e., action units based on predictions of the near future, have to be matched to the current traffic situation to avoid critical events. Scenario recognition due to frequent encounters or distraction is hypothesized to play a role in correct selection of schemata. Entering a traffic conflict or failing the proactive barrier is thus defined by a “mismatch between the selected schemata and the traffic situation at hand, such that early conflict resolution is either unsuccessful or absent altogether” (Markkula et al., 2012, p. 1120). “Bottom-up reflex activation of near-crash avoidance schemata” (p. 1120), called the reactive barrier, may still prevent a crash. For the reactive barrier, visual attention to the road is considered essential to enable reflex activations by visual stimuli such as visual looming. The model thus illustrates, similar to the TCI, that a conflict does not necessarily lead to a collision, that conflict states may be entered frequently for a number of different reasons and that this frequency, related to the incorrect selection of schemata, is influenced by a number of individual and external factors.

Accidents have also been considered as the cause of errors, with the frequency of errors influenced by different accident-related factors (as reviewed by Markkula et al., 2012). Errors can be attributed to different steps of human information processing (as reviewed by Vollrath & Krems, 2011), the central process behind driving (Abendroth & Joisten, 2024). In their review, Siebke et al. (2022) cite different studies with relevance to Rasmussen's error taxonomy of four causes (i.e. why errors occur) and five mechanisms of errors (i.e. how errors occur). The causes and mechanisms of errors include (visual) distraction and attention, task demand and non-responsiveness and can thus be linked directly to other frameworks reviewed here, such as the behavior-based crash-causation model (see below). As stated by the authors, "accidents only occur when errors persist over time or when the time spans in which the driver can react are too short" (p.1421), a notion in line with the relevance of tactical decisions, e.g. to increase the available time budget for reactions by larger following distances. Collision risk has also been investigated as the product of human factors, e.g. age, and (associated) driver limitations such as the usable field of view or speed of cognitive processing (as reviewed by Vollrath & Krems, 2011). Generally, errors occur more frequently because drivers did not perceive relevant information (i.e., information error) than because drivers did not understand what to do in a specific situation (Vollrath & Krems, 2011).

Amongst other already discussed mechanisms, the indispensability of visual attention is also apparent within the behavior-based crash-causation model (CBM), as introduced in a review by Bärgman et al. (2024). The model is included here to enable a further understanding of (human) mechanisms for crashes. It consists for four sub-modules, each named after the rear-end crash-causation mechanism that it describes:

- *Off-road glances* limit the driver's ability to respond to looming lead vehicles and lead to delayed braking responses. Off-road glances are cited as a main contributing factor to (rear-end) crashes, with a large body of literature backing the influence as a crash causation factor. Following Bärgman et al. (2024), their relation to crash outcome is less well investigated.
- When driving *too close* to the lead vehicle, crashes can occur even if the driver's eyes are on the road (see also Siebke et al., 2022).
- *Low deceleration* as an additional crash mechanism describes the finding that drivers will not always brake as hard as possible (as also discussed in Markkula et al., 2016). Independent of delayed responses, hard braking might lower the crash speed or lead to an avoidance of the crash altogether.
- Although the exact contribution of each mechanism to the proportion of crashes is yet unclear, the proportion of some mechanisms can be estimated based on available studies. According to research cited by Bärgman et al. (2024), drivers show *no response* at all due to being sleepy or drowsy in a suspected proportion of 6.6% up to 20% of crashes. These cases result in a maximum of impact speed due the complete lack of mitigating actions.

2.3 Measures for driving performance

An analysis of papers from the systematic literature research that contained measures for driver behavior revealed reaction time (including labels such as time to driver input) to be the most frequently referred to performance metric. This result of the current literature analysis is in line with the relevance of reaction time for crash avoidance. Bärgman et al. (2024) state “that in the literature crash generation causes crashes in various ways, but reaction time is almost always one component [with] reaction time to brake-light onset [being] very often used as a main safety metric” (p. 380). A similar emphasis can be found in Markkula et al. (2012) concerning near-collision situations (see also Markkula et al., 2016): “Maneuver timing has been studied by many researchers, in terms of the *reaction time* from a stimulus to an evasive reaction” (Markkula et al., 2012, p. 1120).

The time taken to perceive a stimulus and act on it is also referred to as perception response time (PRT). “PRT is […] typically seen as a property ascribed to the individual agent, as opposed to being a property of the dynamically evolving situation as a whole. Based on this tradition, Green (2000), in an influential paper, proposed a set of canonical driver response times based on the driver’s degree of expectancy of the event: ‘‘expected’’ events (0.7–0.75 s response time), ‘‘unexpected’’ events (1.25 s) and ‘‘surprise’’ intrusions (1.5 s)” (Engström, Liu, et al., 2024, p. 2). Green (2000) points to limitations of the own review, such as only considering human brake-reaction time data in good conditions (as data from other conditions are rare) and only superficially addressing the complexities of population variability. His central conclusion for this report might be that “there is no single “best-guess” value for brake RT. However, there is sufficient convergence among studies of similar methodology to enable reasonable estimates for specific situations” (Green, 2000, p. 213). One question to be considered should thus be just how specific situations or parameters would need to be to be able to provide a good estimation for driver performance.

Green reports data for *mental processing time* (according to convention termed “perception time”), *brake reaction time* (as the combination of perception and movement time) and finally *stopping time* as the sum of RT and device response time. Generally, response time can be decomposed into a sequence of components, i.e. mental processing time, sensation, perception, response selection and programming, movement time and finally the device response time, not all of which are observable (Green, 2000). Reaction times from 40 studies are provided in the review, including the paradigm used for data collection and the variables investigated in the study. RT estimates are discussed according to effects of

- *expectancy* (faster responses for expected brake events),
- *urgency* (faster responses for shorter time-to-collisions (TTC)),
- *age* (increasing RT with higher age, although strategies for compensation need to be considered),
- *gender* (mixed results) and
- *cognitive load* (e.g., slower RT with use of cellular phones, but effect size varies depending on exact paradigm used).

(Brake) response times have also specifically been collected in controlled on-road studies to be used as reference for driver performance in the case of crashes (“Kölner Modell” and “Dresdener Modell”; see an overview publication by Bäumler, 2009). Like the decomposition by Green (2000), the time between signal onset (brake light) and standstill is here separated into *human aspects* and *vehicle aspects* with different timings attributed to each aspect. Reaction time components are reported for relevant percentiles of the investigated samples (e.g., median, 95%). The collected data consider different visibility and road conditions (nighttime versus daytime; dry versus wet), revealing, e.g., faster reactions to brake light onset during nighttime when surrounding light conditions do not obscure the stimulus (Bäumler, 2009).

PRT is often seen as an individual’s property, but research also stresses the influence of situational factors, above all scenario / kinematic urgency, as the main influence on response times (e.g., Engström, Liu, et al., 2024; Engström et al., 2018). Markkula et al. (2016) analyzed 116 naturalistic rear-end crashes and 241 naturalistic near-crashes, extracted from the Second Strategic Highway Research Program (SHRP 2) and the Analysis of Naturalistic External Datasets (ANNEXT) project. Relating to surprise emergencies as reviewed by Green (2000), the authors state that: “Rather than driver braking in these events being slow reactions to some researcher-defined “hazard onset”, such as brake lights coming on, these reactions may be better thought of as rather fast responses to the visual looming cues that build up later on” (p. 221). The authors refer to the evidence accumulation model by Markkula, with evidence being all types of input indicating the need for, e.g., braking, such as looming or upcoming intersections to explain “the dependencies of reaction timing both on expectancy, as stressed by Green (2000), and on situation urgency, as stressed by Summala (2000)” (Markkula et al., 2016, p. 220).

Although (perception and braking) response time is one of the most frequently used metrics of driver performance for critical scenarios (see above), the concept of perception response time (PRT) is not without debate for the application in natural driving studies. As Engström, Liu, et al. (2024) state, there are two main challenges to the concept of PRT: “(1) The strong situation dependence of the response process, and (2) lack of a principled, generalizable means to define the stimulus” (p. 2). The authors refer to earlier reviews by Engström and other authors, stating that the “average response times varied widely between studies (0.5 s to 1.5 s) and that most (88%) of this variance could be explained by the scenario kinematics implemented in the different studies” (Engström, Liu, et al., 2024, p. 2). The second point of criticism is concerned with the unclear definition of what exactly the driver is supposed to be reacting to, with, e.g., the same stimulus either triggering a response or not, depending on the expectation of how the situation will play out (Engström, Liu, et al., 2024).

Next to the timing of actions in relation to (more or less defined) events, other metrics have been considered to assess the risk in specific scenarios, such as cut-in or car following. Time-headway (THW) and relative velocity were for example used as risk level indicators to classify cut-in maneuvers (Ma et al., 2019; see Kim et al., 2017, for an example using range-range domain). Research has also focused on the sensitivity of measures for specific influences on performance: An exemplary overview over 45 studies and their employed driving performance metrics to indicate distracted driving can be found in the review of Papantoniou et al. (2017), including reaction time, headway, acceleration/deceleration and accident probability. For the analysis of traffic conflicts, surrogate metrics of safety such as the distance to conflict point, TTC, time to accident or the post encroachment time are considered as well as collision probabilities or the risk of collision (Knake-Langhorst et al., 2024; see also the comparison of strengths and weaknesses of surrogate metrics by Lu et al., 2021). Panou (2018) reviewed different driving parameters (static, semi-dynamic and dynamic), including reaction time, THW and TTC, as the basis for modeling longitudinal driver behavior with the goal to personalize collision avoidance warnings.

One approach to counter the fact that crashes are relatively rare events and are even more infrequently captured in data collections is the combination of crashes with near crashes (Wang & Xu, 2019). Song et al. (2021) proposed a classification model for drivers' individual risk levels. They used the *crash and near-crash (CNC) rate* as the label for the risk level classifier and self-reported metrics (driving experience, risk perception, sensation seeking and risky driving behavior engagement) as input for their classification model. The CNC rate standardizes the individual number of crashes and near-crashes by the kilometers travelled in a defined period of analysis. With their classification model, Song et al. (2021) aimed to provide an alternative approach to risk classifications with a high accuracy. As a starting point for this endeavor, the relationships between demographic characteristics and personality traits were analyzed for 3150 drivers from the SHRP2 dataset. Model classifications revealed a high percentage of drivers within the SHRP2 dataset to be low-risk drivers (73.5%) with only 3.0% of drivers classified as high-risk drivers. This proportion of driving risk levels within the dataset might be of importance when using these data for model parametrizations and assuming a certain type of driver population (see Chapter 4).

Papazikou et al. (2017) reviewed different metrics for driving risks and the detection of hazardous driving situations, including braking onset, longitudinal acceleration, lateral acceleration and TTC. They suggest using multiple indictors to identify thresholds for normal driving, i.e., a combination of TTC, longitudinal deceleration and acceleration as well as lateral acceleration. Based on a review of different data sets and analyses (e.g., 100-car study, EURO FOT, UDrive), they identify the threshold TTC for a safety critical event to range between 1.75 seconds and not more than 2.0 seconds and provide further metrics to be considered for the identification of such events. "In summary, it can be concluded that a detection of any deviation from normal driving would not only require the simultaneous measurements of multiple indicators but also the different threshold values per indicator based on traffic conditions and driver demographics" (Papazikou et al., 2017, p. 10). Other approaches to defining threshold values using naturalistic driving study (NDS) data can be found in the review by Ahmed et al. (2022).

Sagberg et al. (2015), reviewing research on driving style, define a continuum between global and specific driving styles, where global driving styles are defined by several indicators and specific driving styles by only one or few indicators. An example for a global driving style is aggressive driving, defined by different behaviors indicative for the same underlying motive, whereas speeding would be considered a specific, habitual behavior (i.e., a specific driving style). The authors further define measures as the “basic signals that are used as input for the calculation of indicators” (p. 1254) and provide examples of measures, indicators and specific driving styles under the global categories aggressive, calm and careful / defensive driving. Further specific driving styles including measures and references are reviewed along the following categories:

- longitudinal control (e.g., speeding; measure: speed),
- lateral control (e.g., left-lane preference; measure: lane choice),
- gap acceptance (e.g., frequent overtaking; measure: passing gap when overtaking),
- visual behavior (e.g., frequent long looks away from road; measures: fixation length and frequency),
- errors and violations (e.g., high frequency of respective actions; measures: use of wrong gear, driving through red traffic light etc.),
- other.

The authors discuss the relation of different driving styles to crash risk and conclude: “There is a need for more research in order to map out these relationships in more detail in order to make quantitative estimates of the predictive power of different driving styles regarding driver crash involvement and to arrive at a clearer understanding of the behavioral mechanisms involved” (Sagberg et al., 2015, p. 1263). Similarly, Wang et al. (2010) conclude that the combination of specific situational factors (e.g. congestion) and different driving styles (e.g. aggressive driving) still needs to be investigated more closely, although the reviewed literature provides indications, e.g., to characteristics differentiating accident and non-accident drivers.

Itkonen et al. (2017) conducted a driving simulator study (N=15) to investigate the connection between different, frequently used metrics of longitudinal control (i.e., THW, acceleration and jerk). Finding a trade-off between jerk and THW, the authors “propose that the correspondence between time headway and jerky driving reflects a trade-off that can be interpreted as an “intensity-calmness” parameter of driving style”. In a slightly different approach, Doubek et al. (2021) conducted an interview study to derive (subjective) characteristics of a good driver, concluding amongst others that a good driver avoids physical limits. Furthermore, good drivers are considered as self-confident, not aggressive and not stressed. While these criteria might serve to select measures to select good or safe populations of drivers, they do not provide explanatory value to crash risks due the selected paradigm. Self-reports and questionnaires can however be used to provide insights on error causes or personality characteristics (e.g., Siebke et al., 2022; Witt et al., 2019). Another example employing the CNC rate and linking drivers’ crash risk to self-reported risky driving behavior (as extracted from the Manchester Driver Behavior Questionnaire) was conducted by Wang and Xu (2019). The study used data extracted from the SHRP2 dataset (from 52 drivers) and linked three risk levels (low, moderate and high) to the probability for different types of violations, lapses and errors during driving. To extract near-crashes from the data, the authors applied five different trigger criteria as defined for the 100-car NDS (Dingus et al., 2006), based on acceleration/deceleration thresholds and

TTC values (or combinations thereof; see also the near-crash definition as referred to by Song et al., 2021).

"To obtain an in-depth understanding of the causes of crashes, three general approaches have been extensively used, namely the retrospective clinical approach, the epidemiological/statistical approach, and the prospective naturalistic driving study (NDS) approach" (Ahmed et al., 2022, p. 106567), with NDS combined with questionnaires considered as the most effective approach by the reviewers. Generally, crash or near-crash events being derived from naturalistic data are valued for offering a higher accuracy than self-reported data (Song et al., 2021). However, habitual driving behavior can also be characterized by self-report metrics in addition to or as a substitute for objective observations, although objective metrics might be preferred as the more unbiased data source. As reviewed by Sagberg et al. (2015), the two types of methods generally yield significantly correlated results: "For speeding behavior, correlations above .60 have been reported, but for other driving styles, the magnitudes of the correlations are often relatively weak" (Sagberg et al., 2015, p. 1270). For different levels of control (cf. TCI; Fuller, 2005), the suitability of methods for data collection differs, with driving simulator studies also suited to provide data in more challenging scenarios for loss of control or collisions and NDS or field operational tests (FOT) providing mostly data on controlled driving (Quante et al., 2021). An overview on different subjective and objective methods to study driving styles can be found in Sagberg et al. (2015), with the objective methods also applicable to driving performance observations in specific scenarios. An evaluation of different paradigms in terms of ecological validity and implications for brake RT can be found in Green (2000).

2.4 Influencing factors on driver behavior and performance

The influences on driver behavior, and ultimately on driving performance, are numerous and have been the subject of many other reviews, e.g. Abendroth & Joisten, 2024, Ahmed et al., 2022, Green, 2000, MacAdam, 2003, Sagberg et al., 2015. The reviewed influences vary, depending on the focus of research. Studies and reviews focus both on the systematic effects of driver capabilities (competences, characteristics and attributes) as well as on systematic effects of driving conditions, as detailed in prior research:

- "*Reaction time estimates have been proposed as functions of a range of parameters: stimulus eccentricity, number of obstacles, nighttime versus daytime driving, age, gender, and the previously mentioned cognitive distraction and stimulus expectancy*" (Markkula et al., 2012, p. 1120).
- *"Driving behavior varies systematically also across different road, traffic, and driving conditions, such as traffic density, road geometry, weather, light conditions, and so on. Drivers may show different patterns of behavior in different conditions*" (Sagberg et al., 2015, p. 1252).

The following tables provide an overview on influences as found in exemplary literature sources and earlier reviews, categorized into four broader categories of factors:

- driver states (Table 2-1),
- driver characteristics (Table 2-2),
- driver personality factors (Table 2-3),
- environmental factors (Table 2-4).

Driver states, such as stress, sleepiness or fatigue, are temporary and fluctuating, reflecting the driver’s current physical and mental condition. Since the driver's state is subject to intra-individual fluctuations, a distinction can be made between influencing factors changing short-term (within minutes or seconds) and medium-term (within hours or days) (Langer et al., 2015). In contrast, driver characteristics describe rather stable, long-term traits, such as age, gender or driving experience, that remain relatively constant over episodes of time (Witt et al., 2019). The third category involves the latent driver personality factors such as thrill-seeking, risk propensity or anxiety (Witt et al., 2019). These categories can be seen as internal attributes of the driver. In addition to these internal factors, external conditions such as road conditions, weather, traffic, and lighting (environmental factors) also affect driving or the driver's response to the situation.

Table 2-1: Overview on driver states with relevance to driver behavior and performance

Factor	**References** (in which factor was investigated or reviewed)
Workload / Individual Resources	Bekiaris et al., 2003; Brandenburg, 2014; Dargahi Nobari & Bertram, 2024; Green, 2000; Green et al., 2004; Hoyos, 1988; Lamble et al., 1999; Lewis-Evans, 2012; Ma et al., 2023; Shinar & Oppenheim, 2011; Xie et al., 2022;
Arousal level / Alertness / Vigilance	Fuller, 2000; Xie et al., 2022
(Visual) Attention / Distraction	Alm & Nilsson, 1995; AlMekhlafi et al., 2020; Bärgman et al., 2017; Bekiaris et al., 2003: Dargahi Nobari & Bertram, 2024; Dingus et al., 2006; Fuller, 2000; Kujala & Lappi, 2021; Lamble et al., 1999; Papantoniou et al., 2017; Pekkanen et al., 2018; Precht et al., 2017; Saifuzzaman & Zheng, 2014: Summala, 2000
Emotions (e.g., fear, sadness, anger) / Mood	Chahine et al., 2022; Dargahi Nobari & Bertram, 2024; Fuller, 2000; Lewis-Evans, 2012; Ma et al., 2023; Precht et al., 2017
Motivation / Goals	Fuller, 2000; Saifuzzaman & Zheng, 2014
Other impairments (e.g., intoxication, drowsiness, fatigue, stress)	AlMekhlafi et al., 2020; Fuller, 2000; Shinar & Oppenheim, 2011; Wang et al., 2010

Not all sources included provide quantitative estimations that could be used to assess the relevance of factors or to provide direct input to mathematical models. Some papers (such as Bekiaris et al., 2003) focus on the (theoretical) relation between factors and are cited here as potential input for the structure of driver models. As the focus of this report is on driver performance models, this categorization presents an attempt to sort the numerous identified influences but does not claim to cover all influences identified by research or to represent the only or best categorization possible. The overview of 117 studies using NDS data by Ahmed et al. (2022) is referenced here as an alternative structure, separating studies into seven distinct topics:

- driver behavior and performance (e.g., car following, lane change, gap acceptance),
- crash and near-crash causation (kinematic factors, roadway factors, driver factors, environmental factors),
- driver distraction,
- pedestrian and bicycle safety,
- intersection and traffic signal related studies,
- detection (object detection, event detection) and
- prediction (crash/near-crash, behavior prediction).

To give a second example for an alternative structure of influences, the review by Wang et al. (2010), focusing on Chinese journals and including 43 studies, established four road safety-related categories of research:

- driver capacity (including physical and mental abilities, reactions, attention, workload),
- driving style (including personality traits, stress, mood),
- driver fatigue (including the influence of driving time, time of day, age, driving experience on driver performance),
- (characteristics of) traffic accidents.

Finally, the following classification approach is suggested by Itkonen et al. (2017):

> *"The heterogeneity among driver-vehicle systems in terms of longitudinal speed control could and should be decomposed into a "psychological component" (probed by our experiment where the vehicle dynamics were identical for all participants), a "vehicle" component (e.g. differences between truck and passenger car driving) and an "ambient" component (visibility, slippery roads). This psychological component would correspond to what in traffic psychology is referred to as driving style."*

Table 2-2: Overview on driver characteristics with relevance to driver behavior and performance

Factor	**References** (in which factor was investigated or reviewed)
Demographics (e.g. age, gender)	Andrews & Westerman, 2012; Bärgman et al., 2017; Brandenburg, 2014; Broen & Chiang, 1996; Casamento-Moran et al., 2022; Cruz Figueira & Larocca, 2020; Green, 2000; Kusano et al., 2015; Liu et al. 2022; Ma et al., 2023; McLaughlin et al., 2009; Mehmood & Easa, 2009; Montgomery et al., 2014; Park & Zahabi, 2022; Sagberg et al., 2015; Summala, 2000; Witt et al., 2018; Witt et al., 2019
Socio-economic characteristics (e.g., education, income, culture, family structure)	Fuller, 2000; Sagberg et al., 2015; Saifuzzaman & Zheng, 2014; Shinar & Oppenheim, 2011
(Driving) Experience & driving routine (gained through driving) / Education & training (gained through formal training)	Bekiaris et al., 2003; Brandenburg, 2014; Fuller, 2000; Hoyos, 1988; Liu et al., 2022; Ma et al., 2023; Precht et al., 2017; Sagberg et al., 2015; Saifuzzaman & Zheng, 2014; Shinar & Oppenheim, 2011; Song et al., 2021; Tselentis et al., 2020; Wei et al., 2024; Witt et al., 2018, 2019
Driving style	Adavikottu & Velaga, 2024; Park & Zahabi, 2022
Limitations / capabilities (e.g., reaction time, physical & mental abilities)	Bekiaris et al., 2003; Fuller, 2000; Ranney, 1994; Sagberg et al., 2015; Saifuzzaman & Zheng, 2014; Wang et al., 2010

Human information processing, sequenced into information acquisition, information processing and information output, is central for the execution of the driving task (Abendroth & Joisten, 2024). Each processing step is subject to an interaction of individual characteristics, competences, capabilities and demand, as defined by the current driving situation and environment. For information acquisition, visual information is the most important input channel during driving (e.g. MacAdam, 2003; Vollrath & Krems, 2011). Apart from vision, vestibular and kinesthetic, tactile and auditory information also play a role (Abendroth & Joisten, 2024; MacAdam, 2003). For each input modality, literature provides general human limitations to perceive and process different stimuli (e.g., Abendroth & Joisten, 2024). Based on a review of Chinese publications, Wang et al. (2010) suggest recommended values for different measures of a safe driver, including static and dynamic visual acuity as well as reaction times.

Table 2-3: Overview on personality dimensions with relevance to driver behavior and performance

Dimension	**References** (in which dimension was investigated or reviewed)
Sensation seeking	Bärgman et al., 2017; Fuller, 2000; Shinar & Oppenheim, 2011; Song et al., 2021; Wang et al., 2010; Witt et al., 2018, 2019
Chronotype	Ge et al., 2020
(State) Anxiety	Wang et al., 2010; Witt et al., 2018; Witt et al., 2019
Law conformity (e.g., number of violations) / Accident rate	Precht et al., 2017; Tselentis et al., 2020; Wang et al., 2010
Risk perception / risk propensity / risk tolerance	Bekiaris et al., 2003; Saifuzzaman & Zheng, 2014; Song et al., 2021; Witt et al., 2019
Aggressiveness	Bärgman et al., 2017; Chahine et al., 2022; Sagberg et al., 2015; Saifuzzaman & Zheng, 2014; Tselentis et al., 2020; Wang et al., 2010; Witt et al., 2019
Driving anger	Witt et al., 2018, 2019

Consequently, factors limiting the capability for visual information acquisition, e.g., the usable field of field (Vollrath & Krems, 2011), have an impact on driving performance and collision risk. Age is among the frequently reviewed factors that influence visual information intake (for a review see Abendroth & Joisten, 2024). Other factors influencing visual perception are driving experience (with less experienced drivers showing less efficient gaze strategies, see, e.g., Abendroth & Joisten, 2024), currently performed (visual) non-driving related activities, increasing the probability for information errors, and visibility, restricted by fog or rain.

In his review, MacAdam (2003) “describes various human characteristics, both in terms of physical limitations as well as certain attributes, that should be incorporated into any serious effort aimed at modeling the control behavior of the human driver” (p. 103). Physical limitations include time delays, perception thresholds to sense information, processing time and cognitive requirements to anticipate and predict ahead. Limits for performance under near-ideal conditions are cited from various publications. Among the relevant human characteristics are preview utilization, learning, anticipation and planning abilities (Mac Adam, 2003). Based on the review, the author lists five essential and six desirable features for driver modeling efforts that aim to “represent or mimic a broad range of driver control behavior” (p. 113), the latter feature set depending on the application. A minimal (essential) representation of a driver should provide for example (MacAdam, 2003, p. 112):

- time transport delays,
- preview to sense upcoming control requirements,
- adaptations to altered vehicle dynamics or operating conditions.

Table 2-4: Overview on environmental factors with relevance to driver behavior and performance

Factor	**References** (in which factor was investigated or reviewed)
Traffic level / traffic density / traffic environment	Duan et al., 2013; Green et al., 2004; Park & Zahabi, 2022; Saifuzzaman & Zheng, 2014; Wang et al., 2019; Xie et al., 2022
Roadway geometry (e.g., road curvature)	Brandenburg, 2014; Ma et al., 2023; Park & Zahabi, 2022; Tawfeek, 2024
Visibility (e.g., due to weather conditions like fog, mist or rain; lightning)	Ali et al., 2021; Bekiaris et al., 2003; Brandenburg, 2014; Brooks et al., 2011; Caro et al., 2009; Dinakar et al., 2021; Fuller, 2000; Ma et al., 2023; McLaughlin et al., 2009; Park & Zahabi, 2022; Precht et al., 2017; Wang et al., 2019; Wei et al., 2024
Situational factors (e.g., urban, rural, and highway, signs, visual elements, surface or passengers)	Bärgman et al., 2017; Bekiaris et al., 2003; Brandenburg, 2014; Fuller, 2000; Fuller et al., 2008; Green et al., 2004; Ma et al., 2023; McLaughlin et al., 2009; Powelleit & Vollrath, 2019; Precht et al., 2017
Expectancy / urgency	Durrani et al., 2021; Green, 2000; Markkula et al., 2016; Powelleit & Vollrath, 2019; Summala, 2000
Object characteristics (including size and surface textures)	Liu et al., 2022
Situational kinematics (also due to behavior of other road users, e.g. relative speed, acceleration)	Dinakar et al., 2021; Fuller, 2000; Fuller et al., 2008; Wang et al., 2019
Vehicle characteristics (e.g., type, size)	Bekiaris et al., 2003; Fuller, 2000; Fuller et al., 2008; Ma et al., 2023; Xie et al., 2022

2.5 Frameworks for explaining driving performance

Despite approaches for a more consolidated theory to explain driver behavior (e.g., predictive processing, see Engström et al., 2017), there is to date no unifying framework of driver behavior (Lewis-Evans, 2012). “This could potentially reduce the impact and adoption of traffic safety interventions due to mixed messages and conflicting paradigms." (Lewis-Evans, 2012, p. 160).

Different reviews are available with similar categorizations of frameworks to explain driver behavior (see Table 2-5), partly reviewing earlier categorizations and partly restructuring older differentiations (e.g., Lewis-Evans, 2012; Michon, 1985; Negash & Yang, 2023; Ranney, 1994, Shinar & Oppenheimer, 2011). Some of the classifications reviewed in Table 2-5 have been further grouped into meta-categories, like functional (motivational and information processing models) and taxonomic models of driving behavior (Michon, 1985; see also the review by Ranney, 1994) or descriptive (hierarchical and control loop models) and functional (see above) models (Shinar & Oppenheim, 2011). Generally, there seems to be a stronger agreement in literature regarding the different categories of frameworks than concerning the preference for a specific type of framework. One critical aspect to compare the different frameworks includes how well they can be used to make predictions about driver behavior or generate testable hypotheses, concerning the topic of falsification (as reviewed, e.g., by Lewis-Evans, 2012; Shinar & Oppenheim, 2011).

Table 2-5: Overview over driver behavior theories and frameworks based on categorizations in earlier reviews.

Classification	**Description** (and criticism)	**Classification / description found in**	**Examples**
Task analysis	• Inventories of (sub)tasks for automobile driving	Michon, 1985; Negash & Yang, 2023	Task analysis by McKnight & Adams
Individual differences / Trait models (taxonomic models)	• Individual accident involvement by identifying stable traits • Criticized for being descriptive (post-hoc) rather than predictive	Negash & Yang, 2023; Michon, 1985; Ranney, 1994	Accident proneness
Motivational models	• Risk (perception) as a key factor: "driving is self-paced and […] drivers select the amount of risk they are willing to tolerate in any given situation" (Ranney, 1994, p. 739) • Criticized for a lack of cognition and specific mechanisms, preventing testable hypotheses	Negash & Yang, 2023; Ranney, 1994; Shinar & Oppenheim, 2011; Lewis-Evans, 2012	Risk-threshold model, risk compensation model, zero-risk-model, comfort zone model

Information processing models (also called: cognitive rule-based models)	• Human behavior as a result of (sequential) processing stages, generally: perception; decision making; response selection; response execution • Automaticity and (multiple) resources as key terms • Rule-based models: If-then application of chosen rules and application of schemata	Abendroth & Joisten, 2024; Markkula et al., 2012; Ranney, 1994; Shinar & Oppenheim, 2011; Lewis-Evans, 2012	Models by Abendroth; Wickens & Hollands; SOAR cognitive architecture
Hierarchical (control) models	• Driving tasks itemized and listed in hierarchical stages, in which memory-driven and information-driven decisions are required • Task execution based on stored knowledge, rules, and skill sets	Negash & Yang, 2023; Ranney, 1994; Shinar & Oppenheim, 2011	Classifications by Michon, Donges, Rasmussen
Other frameworks based on:	• Perception / attention mechanisms (visual search, e.g. Ranney, 1994; visual looming) • (Prediction) Errors (Ranney, 1994; predictive processing, Engström et al., 2017, 2024) • Attitude theories (e.g., theory of planned behavior by Ajzen; see Lewis-Evans, 2012)		

In a theoretical paper, Engström et al. (2017) promote *predictive processing* "as a unifying framework" (p. 1) for different human factors theories and models in the automotive context. Amongst others, the authors argue how concepts such as mental models, visual guidance or situation awareness (SA; here specifically: updating the situation model and prediction as a central aspect of SA), as well as the SEEV model can be integrated into the predictive processing framework. Of most relevance in the context of this chapter is, however, their integration of motivational models into this unifying framework by providing an explanation of "how driving behavior is governed by emotions and feelings" (p. 30). "The central idea underlying predictive processing is that the key function of the brain is to capture statistical regularities in the environment and in the body by continuously trying to predict its own sensory input and acting on the resulting prediction errors (i.e. the mismatch between the predictions and the actual sensory input)" (Engström et al., 2017, p. 3). In the paper, three central principles are introduced in more detail to explain predictive processing in the driving context, accounting for perception and action (*active inference*), the probabilistic weighting of input and predictions (*precision*) and learning (*model tuning).*

A likeminded, but different approach to define an underlying principle and generalize behavior predictions to multiple scenarios is, for example, given by Kolekar et al. (2020) who proposed the concept of the Driver's Risk Field (DRF). The authors compared their model predictions to results extracted from literature for seven scenarios such as car following, overtaking or oncoming traffic.

2.6 Conclusions

To summarize, driving performance is highly variable and a product of numerous influences which have been documented in a large body of literature. Driving performance differs intra- and interindividually as well as systematically between different external settings. Consequently, driving performance has been regarded as an individual characteristic or as a product of internal processes (e.g., expectation; Green, 2000; see also the now largely discarded concept of accident proneness; Sagberg et al., 2015) as well as a product of situational characteristics that trigger actions (e.g. scenario kinematics, Engström, Liu, et al., 2024; Engström et al., 2018). Others have suggested a selection of essential limitations and attributes to be considered (MacAdam, 2003).

Visual information seems especially important for good driver performance, with information quality being subject to limitations such as the usable field of view, attention to the road and environmental conditions (e.g. fog, rain). Thus, for driver modeling, realistic assumptions have to be set as to what a human driver can perceive and process in a certain situation or amount of time, based both on physiological limitations for an individual or population and the current condition or driver state. Svärd et al. (2021) state accordingly: “Since off-road glances are an inherent part of everyday driving, [the] assumption [note: that drivers will keep their eyes on the road] makes the models less realistic” (p. 1). When modeling driver performance, it would be simplistic to ignore the various influences on driver behavior and performance and assume, for instance, a general, situation independent response time (Svärd et al., 2021; see also Engström, Liu, et al., 2024; Lindorfer et al., 2018). Similarly, Itkonen et al. (2017) state: “Average behavior, “ideal” forms, or population means may capture overall central tendencies, but […] it is necessary to take into account the fact that real behavior rarely follows a single, simple rule”. Additionally, Huguenin and Rumar (as referred to by Lewis-Evans, 2012, p. 18) “state that the models which have been put forward have tended to be either so broad as to be unusable for generating useful predictions or so specific as to only explain certain small parts of the driving task”.

Measuring driving performance in the field can present its own methodological challenges (e.g., stimulus onset for reaction time definitions; Engström, Liu, et al., 2024). Furthermore, good driver performance is more than just collision avoidance, considering, e.g., tactical decisions such as speed, distance or driver distraction. Different types of human errors can occur and increase the probability of a crash, but errors or the loss of control do not necessarily lead to crashes (as also illustrated by the term *lucky escape* in the TCI, see Fuller, 2005). Furthermore, crashes can occur without an error by the driver (for a review, see Siebke et al., 2023). Next to the timing and scaling of driver actions, the probability of different tactical or collision avoidance strategies should also be considered for a realistic understanding of successful performance, as drivers do not necessarily conduct the physically most feasible action (e.g. steering versus braking versus combined steering and braking).

As no theory exists to explain all driving behavior in all kinds of scenarios (Lewis-Evans, 2012), abstractions and simplifications are necessary to investigate and explain driver behavior. In general, models “denote how we represent the way humans behave during driving. [They] describe the corresponding representations of driver behavior” (Negash & Yang, 2023, p. 22790). Different theories exist to explain when and how drivers enter or react to conflicts. The description and prediction of human driver behavior by means of models is one approach to help understand behavior related to crashes (Markkula et al., 2012). This chapter, meant to provide a basis for the review of driver performance models in this report (see Chapter 3), is an attempt to categorize the more prominent frameworks and theories for driver behavior and collision avoidance. For a deeper understanding of each theory, we would like to refer to the original reviews and papers as cited above.

In conclusion, research provides recommendations and clues as to what should be considered to represent or model realistic driving behavior (e.g., MacAdam, 2003). However, a trade-off between realism and complexity is unavoidable. Additionally, different parameters and thresholds have been provided to separate good from average from bad performance or low from normal from high risk levels. Which characteristics and measures are most relevant depends however on the current goal and context.

3 State-of-the-art: Reference models

The term *reference model* refers to driver models being used as benchmarks in the safety assessment of automated vehicles. Before focusing on reference models in later sections of this chapter, we first provide a brief introduction to driver models in general.

Driver models are mathematical or algorithmic frameworks designed to simulate how a human driver interacts with their vehicle and other traffic participants on the road. These models aim to replicate the complex cognitive processes required for a human driver to navigate various challenging traffic environments and translate them into formalized, programmable structures. Driver models vary widely in their level of abstraction and the aspects of the driver's decision-making process and control actions they model. There are simple rule-based approaches that define deterministic responses, as well as complex data-driven methodologies that strive to closely mimic human driving behavior.

The scope and utility of driver models extend to a wide range of applications. They play a pivotal role in vehicle development, particularly in the design, testing, and validation of advanced driver assistance systems (ADAS) and automated driving functionalities. Driver models are also used in traffic simulation, traffic management, and road safety research. Additionally, they are employed in the design of human-machine interfaces and the evaluation of driver behavior in various traffic scenarios.

3.1 Driver model categorization

To make sense of the wide field of driver modeling, we will first discuss different methods of categorization. This will help clarify where driver models differ from each other and for which applications different models might be more suited. The literature offers various approaches to categorize and structure driver models. In this section, we present different methods of categorization.

One way to differentiate between driver models is by the control actions they allow. Driver models that directly control vehicle dynamics can be divided into models in the longitudinal or lateral domain. The longitudinal domain includes models that control the speed of the vehicle, such as the *Intelligent Driver Model (IDM)* (Treiber et al., 2000). The lateral domain includes models that control the lateral position of the vehicle, such as the Two-Point Visual Control Model of Steering (Salvucci & Gray, 2004). The same is true for the level of tactical decision making. One example is the MOBIL lane change model (Kesting et al., 2007), which is a model for tactical decision-making in the lateral domain.

Another possible categorization is to distinguish between microscopic and macroscopic driver models. Microscopic models focus on the individual driver and their interactions with the vehicle and the environment. These models are often based on principles of cognitive psychology and human factors research. Macroscopic models, on the other hand, treat the driver as a component of a larger traffic system and focus on aggregate traffic flow and dynamics. These models are often used in traffic engineering and transportation planning. For the purposes of this work, we will focus on microscopic driver models, as they are more relevant for understanding and predicting individual driver behavior, which is needed in the context of reference models for automated driving systems.

We can also distinguish by the type of data sources used in model parameterization, as well as the underlying assumptions about driving behavior. For example, some models are based on data collected using controlled experiments, such as driving simulator studies. Others are based on data from naturalistic driving, while some are purely theoretical constructs.

In the following, we go into more detail on the categorization of driver models by driving task and by model structure. This will help to understand the different approaches to driver modeling and how they can be applied to different aspects of driving behavior.

3.1.1 Categorization by driving task

Driver models can generally be classified based on the type of driving task they represent. Several frameworks exist for structuring these tasks. Michon (1985) categorizes driving tasks into three hierarchical levels: Strategic, Tactical, and Operational. These levels provide a systematic approach to analyzing and modeling complex human driving behavior by describing distinct aspects and decision-making stages of driving. Similarly, Donges (1982) divides driver behavior into three levels: Navigation, Guidance, and Stabilization. These levels align closely with Michon’s categorization.

- *Strategic Level (Navigation)*: The strategic level pertains to long-term decisions and planning that a driver makes before or during a journey. These decisions primarily involve route selection, destination choice, and overall driving strategy. Examples include choosing a route to avoid traffic congestion, planning stops along the way, or deciding between taking a highway or a scenic route. Such decisions typically have a time horizon ranging from minutes to hours and are influenced by personal preferences, traffic conditions, weather, and the desired destination.
- *Tactical Level (Guidance)*: The tactical level involves real-time decisions made during driving to maneuver the vehicle. This level focuses on interactions with other road users and the immediate traffic environment. Common examples include lane changes on multi-lane roads, overtaking slower vehicles, navigating roundabouts, or adjusting speed according to traffic flow. The time horizon for decisions at this level ranges from seconds to minutes and is influenced by factors such as traffic density, the behavior of other drivers, road conditions, and traffic signals.
- *Operational Level (Stabilization)*: The operational level addresses the lowest level of decision-making, dealing with direct control actions necessary to keep the vehicle in motion. This involves immediate, fine-motor control tasks performed by the driver, such as steering, accelerating, braking, shifting gears, and fine-tuning speed and direction. Decisions at this level are made within a very short time frame, from milliseconds to seconds, and are influenced by the vehicle’s current dynamics, road surface conditions, and visibility.

3.1.2 Categorization by theoretical foundation

The model structures presented by Lemmer et al. (2023) provide a comprehensive overview of various approaches to modeling driver behavior and traffic dynamics. These models can be broadly categorized into three main types: Traffic Flow Models, Control Theoretic Models (with subcategories of Non-Interactive and Interactive Control Theoretic Models), and Data-Driven Models. Each category has specific applications and methodological approaches for analyzing and predicting driver behavior.

- *Traffic Flow Models*: These models focus on simulating and analyzing traffic flow on roads and highways. They treat traffic as a continuous flow, akin to a fluid, and model the dynamics of traffic at an aggregate level. These models are particularly useful for describing and predicting traffic density, speed, and flow within large transportation systems.
- *Control Theoretic Models*: These models leverage principles from control theory to model and manage driver behavior. They consider the vehicle and driver as a dynamic system aiming to achieve or maintain specific target states, such as a desired speed, position, or distance from other vehicles.
- *Data-Driven Models*: Data-driven models rely on large datasets and employ machine learning and artificial intelligence techniques to model and predict driver behavior. These models are especially effective for capturing complex behavior patterns that are challenging to describe with traditional analytical or control-theoretic approaches.

3.2 Driver model components

Driver models typically consist of several key components encompassing *perception*, *cognition*, and *action*. *Perception* refers to the model's ability to gather information from the environment and the vehicle, often through a connected simulation. *Cognition* represents the driver's capability to process this information and make decisions based on it. These decisions, in turn, result in *actions* that influence the driver, the vehicle, and the surrounding environment.

These components collectively address various aspects of the driving task. Depending on the model's purpose, it may aim to represent the entire driving task comprehensively or focus on specific elements of it. Furthermore, certain components within the model can be highly abstracted, depending on the level of detail required for the application.

This variability in scope and abstraction results in a wide range of driver model types, each structured differently to suit its intended application. Some models may offer a holistic representation of the driving process, while others may specialize in isolated aspects, such as decision-making or control, based on the specific goals of the simulation or study.

3.3 Structure of reference models

In this section, we discuss the overall structures of driver reference models and the elements that they contain. Understanding the overall structure that underpins these models helps us to understand the different approaches the models take. We will go into more detail on the structure of the individual sections in their respective sections. All the driver reference models we discuss contain some basic common elements. These include, at the most basic level, a stimulus, a reaction time, and a response (Wang, Guo, Zhao, et al., 2024).

Common stimuli for more basic reference models can be the time-to-collision (TTC) for a brake response or the wandering distance for a steering response. The reaction time is the time it takes for the driver to react to the stimulus. In more basic models, the stimulus tends to be deterministic. An example would be the reference model proposed by (UNECE, 2021). Other models vary the response time based on the driver's surprise (Engström, Liu, et al., 2024) or the criticality of the situation (Jurecki & Stańczyk, 2009). The response is the actual action taken by the driver in response to the stimulus.

Cognitive models tend to be more complex and include additional elements such as perception, decision-making, and control. Perception is the process of interpreting the stimulus. Decision making is the process of selecting the appropriate response based on the stimulus and the current state of the driver. Control is the process of executing the response. These models are often based on cognitive psychology and human factors research, making them more intricate. Examples of cognitive models include the Stochastic Cognitive Model (SCM) (Fries et al., 2022) and the Driver Reaction Model (DReaM) (Siebke et al., 2022).

In addition to these elements, advanced cognitive models may incorporate factors such as driver experience, fatigue, and emotional state, which can significantly influence driving behavior. These models aim to provide the ability to change driving characteristics to form a more comprehensive understanding of driver behavior by considering a wider range of variables and their interactions. This makes them particularly useful when the analysis of driver failures or the prediction of driver behavior in complex scenarios is required.

3.4 Criteria for model analysis

In order to allow for a comparison of the different models we have defined a series of analysis criteria. These criteria help to understand the focus of different models and how they are intended to be used. Some of the criteria have already been compiled by Wang, Guo, Yu, et al. (2024) in a similar form.

Scope of Application: The application scope of a driver performance model describes the contexts or fields in which the model is utilized. Examples include simulating driver behavior in automated driving systems, developing driver assistance systems, conducting traffic safety analyses, or investigating specific scenarios such as urban traffic or highway driving.

Modeling Approach and Model Type: The modeling approach refers to the methodology used to describe and simulate driver behavior. This can involve rule-based models, probabilistic models, agent-based simulations, machine learning techniques, or physical-mathematical models. The model type specifies whether the approach is deterministic or stochastic.

Definition of Human Reference: This aspect describes how the human driver is represented as a reference within the model. It can involve a generic representation of an average driver or be based on specific data from real drivers to ensure a realistic simulation. It also specifies whether and how individual differences among drivers – such as reaction times or risk tolerance – are incorporated.

Behavioral Coverage: Behavioral coverage outlines which aspects of human driving behavior are captured by the model. These include fundamental driving tasks such as lane keeping, distance regulation, braking and acceleration maneuvers, decision-making at intersections, responses to unforeseen events, and distractions or fatigue.

Scenario Coverage: Scenario coverage describes the driving situations that the model addresses. These can range from simple, isolated scenarios like merging or exiting traffic to more complex ones, such as dense urban traffic, construction zones, challenging weather conditions, or interactions between manual and automated vehicles.

Modeled Influencing Factors: This section identifies the factors influencing driver behavior that are accounted for in the model. These may include driver-related factors such as stress, attention levels, or physical condition.

Theoretical Basis: The theoretical basis outlines the scientific theories, models, or hypotheses underpinning the driver performance model. These can stem from psychological, behavioral, or cognitive science frameworks. Examples include control theory, decision theory, or human information processing models.

Parameterization: The parameterization describes how the model's parameters are defined and adjusted. This can involve empirical data, experiments, expert assessments, or machine learning techniques. Often, real-world driving data is used to determine parameters such as reaction times, steering behavior, or braking intensity. Additionally, this section specifies the data sources used to parameterize the model. Potential sources include driving simulators, real-world driving data (e.g., from vehicle fleets), laboratory studies, experiments with participants, accident reports, or traffic data from monitoring systems such as infrastructure sensors or drones.

Model Input and Output: This criterion outlines what information is needed by the model apart from its parameterization, and in what way the model provides information about the human behavior.

Validation: Validation describes how the accuracy and reliability of the model are assessed. Typically, this involves comparing model predictions with real-world driving data or experimental results. Successful validation demonstrates that the model can reliably simulate real driver behavior.

Accessibility: Accessibility refers to how easily the model structure can be understood and the model itself implemented. Key factors include if the model is open-source, if the source code is available, if model equations and parameters are available and if the model is well-documented. Accessibility is crucial for the model to be used and understood by researchers and developers.

3.5 Model discussion

In the following section, the identified models from the literature review are presented. For each of the models, a table with the corresponding analysis criteria is given. We have divided the models into different categories based on their modeling approach. The categories are *rule-based models, reaction time models, tactical decision models, data-driven models, agent models,* and *cognitive models*. Since the structure of driver models can vary greatly, there are no hard boundaries between the categories, and some models could be classified into multiple categories. We have chosen the assignment categories based on the main focus of the model and the opinion of their respective authors, where available. The main models analyzed for the different categories are given in Table 3-1. Additional models are mentioned in the sections of related models when appropriate.

Table 3-1: Analyzed models in the different model categories

Category	**Model**
Rule-based models	Responsibility-Sensitive Safety (RSS) model, Safety Force Field Model (SFFM)
Reaction time models	Skilled Human Performance Model, Fuzzy Safety Model (FSM), Driver Model by Jurecki et al., The Non-Impaired Road User with their Eyes ON the Conflict (NIEON) Model
Tactical decision models	Active Inference Model, K-LC, D-LC, Careful and Competent Driver Model for Highway Merging (CCDM2)
Data-driven models	Affordance Competition Hypothesis Model
Agent models	RE:SIM, SimDriver, GeoScenario Simulated Driver Vehicle (SDV) Model
Cognitive models	DReaM, Stochastic Cognitive Model (SCM), CogniBot, COSMODRIVE

Distinguishing between models that qualify as driver reference models for AD and those that do not specifically qualify for this purpose can be challenging. Extensive research has integrated human factors into different driver modeling approaches, enhancing the accuracy of these models in reflecting real-world driving behavior.

Notable examples include the Human Driver Model (HDM), which extends the Intelligent Driver Model (IDM), a simple car-following model (Treiber et al., 2000), to account for human factors such as reaction times, estimation errors, and spatial and temporal anticipation (Treiber et al., 2006). Another example is the car-following model proposed by Pekkanen et al. (2018), which integrates driver attention by modeling the uncertainty of driver actions, such as acceleration choice. In this model, driver attention is triggered when uncertainty exceeds a predefined threshold. Actions are determined through state estimation, comparing the model's environmental observations with predictions from different potential states.

The Cologne Reaction Time Model ("*Kölner Modell"*) is a model describing driver reaction times during emergency braking situations. It was developed in the 1980s by an interdisciplinary commission and was primarily described by Burckhardt (1985). The model divides the emergency braking process into several phases: gaze adjustment time, basic reaction time, execution time, response time, threshold time, and full braking time. While the first three phases are driver-dependent, the last three refer to vehicle-specific parameters. The perception time is not explicitly considered in the model (Bäumler, 2009). To empirically determine reaction times, realistic experiments were conducted in which test subjects drove behind a leading vehicle and had to react to the illumination of the brake lights. The study measured different phases of the reaction process, including basic reaction time, execution time, and gaze adjustment time, as well as the impact of corrective saccades. The results provided insights into how drivers perceive and respond to sudden braking signals under controlled conditions (Bäumler, 2009). For pedestrians entering from the side, reaction times were assessed under ideal visibility conditions, focusing on clear signals such as illuminated brake lights. The modular structure of the model enables a step-by-step analysis of reaction processes and supports the quantitative evaluation of traffic-related factors (Bäumler, 2009).

While these models incorporate human factors, they have not been explicitly designed or used as simulation-based benchmarks for automated driving (AD) systems. In the following discussion, we focus on models specifically designed or applied for this purpose.

3.5.1 Rule-based models

Rule-based models are designed to provide operational requirements for AD functions. These requirements can be used to define preventable and unpreventable conditions, providing, a performance requirement that can be used as a reference for AD functions (Mattas et al., 2022).

Responsibility-Sensitive Safety (RSS) model

The objective of the Responsibility-Sensitive Safety (RSS) model is to ensure the safety of automated driving systems (ADS) through mathematical proofs. RSS safety rules R consist of a pair comprising a safety condition C and a proper response P. The safety condition C is a mathematical expression that must be directly verifiable without relying on future values. The proper response P is a control strategy designed to ensure safe driving. These pairs need to be defined individually for each driving scenario. In theory, to achieve 100% safety, the collection of pairs must encompass all possible driving scenarios, a requirement that poses practical challenges (Hasuo, 2022).

RSS can complement Adaptive Cruise Control (ACC) systems (Hasuo, 2022; Xu et al., 2021). This has been explored in simulator studies (Hasuo, 2022). Furthermore, RSS can be applied to address questions of liability in accident scenarios (Hasuo, 2022).

RSS operates under the assumption that all road users adhere to the following principles: avoiding rear-end collisions, refraining from unsafe cut-ins, observing right-of-way rules, driving cautiously in areas with limited visibility, and avoiding accidents unless doing so would cause another collision. Adhering to these behavioral assumptions is essential for ensuring safety. Additionally, if a road user follows all these rules, RSS asserts that they cannot be deemed at fault in an accident. This aspect is particularly significant for automated vehicle manufacturers in determining liability (Hasuo, 2022).

The RSS model still retains some parameter values that can be adjusted to model more human-like performance. These include the brake reaction time of the model, as well as minimum and maximum accelerations. Using longer reaction times, however, will make the model respond more conservatively, as it still ensures safe driving.

Table 3-2: Analysis Criteria for the Responsibility-Sensitive Safety (RSS) Model

Criterion	**Description**
Application Scope	RSS can be used for collision avoidance in ADS. Additionally, it can be combined with an ACC system, enabling improvements in ADS performance (Hasuo, 2022).
Modeling Approach	RSS is a rule-based model consisting of pairs of safety conditions and proper reactions (Hasuo, 2022).
Definition of Human Reference	No direct human reference is used. Instead, the model tries to ensure collision free driving based on mathematical principles.
Behavioral Coverage	RSS covers rules for tactical decision-making, as well as longitudinal control. RSS has been used for car-following scenarios, as demonstrated by Chai et al. (2020), Hasuo (2022), and Xu et al. (2021).
Scenario Coverage	The model has been applied by Chai et al. (2020), Hasuo (2022), and Xu et al. (2021) in car-following scenarios. However, other scenarios should also be feasible, provided appropriate safety rules are created.

Modeled Influencing Factors	Reaction time is considered within the model.
Theoretical Basis	The RSS is a rule-based model.
Parameterization	Xu et al. (2021) used a non-dominated sorting genetic algorithm (NSGA-II) for model calibration. Chai et al. (2020) used statistical data from the Shanghai Naturalistic Driving Study (SH-NDS). Xu et al. (2021) utilized selected scenarios from the SH-NDS as the basis for NSGA-II calibration.
Model Input and Output	Model Inputs are the speed of the subject vehicle, as well as lead vehicle. Output is the minimum safe distance to avoid a crash under any circumstances.
Validation	Xu et al. (2021) validated the model using original scenarios from the SH-NDS and compared an ACC system to a combination of RSS and ACC. The RSS and ACC combination improved the overall safety performance of ACC and detected hazardous situations earlier than human drivers. Chai et al. (2020) conducted validation through a simulator study, comparing an ACC system to a combination of RSS and ACC. Participants perceived the RSS and ACC combination as safer than ACC alone.
Accessibility	The rule-based character of the model makes it very simple to implement. Different implementations and parameters are available.

Safety Force Field Model (SFFM)

The Safety Force Field Model (SFFM) represents the states of actors as time-dependent functions, describing their properties at a given moment and identifying the set of actors relevant at that time. This forms the control model, which is a function dependent on the state of an actor, the time, and the control parameters. Possible control parameters include steering and braking (Nistér et al., 2019).

Each actor has a safety procedure, defined as a family of control instructions. If all actors adhere to their safety procedures, collisions are avoided. Actors occupy points within a space (2D or higher-dimensional), and their occupied points along their trajectory over time are referred to as occupied trajectories. To execute their safety procedure, actors require these points. An unsafe set of points arises when two actors share the same occupied points. Conversely, a safe set of points is where no overlap occurs.

The model introduces a *safety force field*, where the safety force field of one actor *acts* on another. Instead of considering multiple pairs of actors simultaneously, only one pair is analyzed at a time. The safety force field is described using a “bump function” (Nistér et al., 2019).

Some additional assumptions in the SFFM include:

- *Visibility*: The model distinguishes between visible and invisible actors. For worst-case scenarios, invisible or not-yet-visible actors are also considered, provided they do not assume extreme states. Extreme states are excluded to avoid overly defensive driving by the actors.
- *Latency and Discretization*: The model accounts for delays and calculates the set of possible points where actors could be located based on latency (Nistér et al., 2019).

The SFFM determines whether and to what extent an actor violates safety requirements. Additionally, the model can be extended with further aspects for enhanced functionality (Nistér et al., 2019).

Table 3-3: Analysis Criteria for the Safety Force Field Model (SFFM) (Nistér et al., 2019)

Criterion	**Description**
Application Scope	The SFFM aims to provide a safety layer for automated vehicles, ensuring compliance with safety requirements.
Modeling Approach	The safety procedures can be interpreted as rules, making the modeling approach rule-based.
Definition of Human Reference	The model aims to prevent collisions with other road users through the use of safety measures. It also considers potentially invisible actors to model anticipatory driving behavior.
Behavioral Coverage	The SFFM seeks to prevent collisions by employing braking and steering maneuvers as part of its safety procedure.
Scenario Coverage	No specific scenarios are described in the foundational paper, but the model is designed to address safety in general traffic situations (Nistér et al., 2019).
Modeled Influencing Factors	Attentiveness is considered in the model.
Theoretical Basis	The SFFM is a rule-based model.
Parameterization	Only the theoretical foundation of the model is described in (Nistér et al., 2019). No parameterization or validation is

	provided, and no additional literature was found to address these aspects.
Model Input and Output	The inputs to model are the states of all dynamic actors and static elements, which includes position, direction and velocity. The output of the model are control policies which represent the change in state over time of an actor.
Validation	No information on model plausibility is available.
Accessibility	The general model equations are given, but no parameters are provided. The model itself has only been released to select users (Suk et al., 2022).

3.5.2 Reaction time models

Reaction time models are used to model the delayed response to a stimulus the driver has perceived (Siebke et al., 2022). They are well suited to represent driver behavior in accident scenarios (Siebke et al., 2022) and can be used to define a performance requirement (Wang, Guo, Yu, et al., 2024).

The Skilled Human Performance Model

The Skilled Human Performance Model, as defined in UNECE Regulation 157, is designed to emulate the performance of a skilled and attentive human driver. Its purpose is to establish the threshold at which an accident becomes unavoidable in certain critical scenarios. This threshold is then used to evaluate the safety of Automated Lane Keeping Systems (ALKS) (UNECE, 2021).

The model is specified in the UNECE Regulation 157 for ALKS. Importantly, this regulation defines unreasonable risk as “the overall risk for the driver, vehicle occupants and other road users which is increased compared to a competently and carefully driven manual vehicle” (UNECE, 2021). The driver model is proposed as a tool to allow for this comparison to be made. Additionally, the regulation differentiates between preventable and unpreventable scenarios, with unpreventable scenarios being defined as those scenarios where a competent and careful human driver could not avoid an accident. ALKS systems are expected to outperform human drivers by resolving all preventable scenarios.

The model assumes the driver’s response is limited to braking and divides this response into three functional segments:

- *Perception:* Detection and recognition of a hazard.
- *Decision:* Assessing the situation and determining the appropriate action.
- *Reaction:* Execution of the action, such as braking.

The model incorporates a risk perception point, which acts as the trigger for when the driver first recognizes a critical scenario. These points vary depending on the scenario. Three scenarios are defined for this model: cut-in, cut-out, and deceleration of a lead vehicle. For cut-in and cut-out scenarios, the risk perception point is defined as a wandering point in the lane for the challenger vehicle. For the deceleration scenario, the risk perception point is the time to collision (TTC) between the two vehicles.

To represent the *Perception* and *Decision* phases, the model defines reaction times that characterize human drivers. These include the risk evaluation time and the time interval between completing perception and initiating deceleration. For the *Reaction* phase, the model specifies a jerk time until full deceleration and the deceleration value itself.

Additionally, the model can be used in conjunction with an Automated Emergency Braking (AEB) model to support the human driver.

The model output was analyzed by (Olleja et al., 2024) by comparing with real-world data from the SHRP2 data set. It was found that the model causes crashes for multiple scenarios that did not cause crashes for the human drivers in the data set. This puts into question how well the model really represents skilled and attentive human drivers.

A similar model was implemented by Volvo for safety assessment and comparison to an automated driving function (Rothoff et al., 2019).

Table 3-4: Analysis Criteria for Skilled Human Performance Model (UNECE, 2021)

Criterion	**Description**
Application Scope	Defines the boundaries of scenarios where human intervention could prevent accidents versus those that are inherently unavoidable. This criterion emphasizes the use of a skilled human as a reference point to evaluate system performance.
Modeling Approach	Combines empirical data on human reaction times with a realistic maximum deceleration value to create a model that mirrors skilled human responses under specific conditions.
Definition of Human Reference	The model is designed with a highly skilled and attentive human driver in mind as the benchmark for performance.
Behavioral Coverage	Focuses exclusively on the driver’s braking response as the primary reaction in critical scenarios, excluding other actions such as steering.

Scenario Coverage	Evaluates performance in a range of predefined traffic scenarios, including cut-in, cut-out, and deceleration events.
Modeled Influencing Factors	Does not model any influencing factors apart from time to perception, time to decision, time to reaction, as well as the reaction intensity.
Theoretical Basis	The model’s foundation lies in the representation of human reaction times and reaction intensity.
Parameterization	Parameters are determined through direct observation and measurement, using data from different driving studies. Relies on data from a simulator studies involving Japanese drivers and experimental results from the National Highway Traffic Safety Administration (NHTSA).
Model Input and Output	Input are initial velocities and relative distances of ego and lead vehicle, both in longitudinal and lateral direction depending on the scenario. Output can be pedal depression or deceleration depending on model set up.
Validation	The validity of the model has been critically reviewed, as highlighted in (Olleja et al., 2024), where questions regarding its ability to actually represent competent human drivers have been raised.
Accessibility	The model is designed with a straightforward structure, making it easy to understand and implement. All parameters are clearly documented, ensuring model results can be reproduced.

Fuzzy Safety Model (FSM)

The Fuzzy Safety Model (FSM) simulates a driver who employs defensive driving and early reactions to potential hazards to avoid critical situations. The aim is to enhance Advanced Driver Assistance Systems (ADAS) functions, such as distance regulation and braking maneuvers, in cut-in, cut-out, and car-following scenarios where there is a risk of collision. The model is based on the Surrogate Safety Metric (SSM) extended with fuzzy logic (Mattas et al., 2022).

The FSM performs a longitudinal distance evaluation at each simulation step to assess whether a situation is safe, potentially unsafe, or critical. In cut-in scenarios, a lateral distance evaluation is also conducted to determine whether the cutting-in vehicle might collide with the ego vehicle laterally or merge with insufficient clearance ahead of the ego vehicle. A temporal safety margin is incorporated into these evaluations (Mattas et al., 2022).

Two metrics are used in the longitudinal distance evaluation:

- *Proactive Fuzzy Surrogate Safety Metric (PFS)*
- *Critical Fuzzy Surrogate Safety Metric (CFS)*

Both metrics range in value from 0 to 1. A scenario is considered non-critical when both metrics are zero (Mattas et al., 2022).

The Proactive Fuzzy Surrogate Safety Metric (PFS) evaluates safety based on the speed of the ego vehicle, the speed of the cutting-in vehicle, the reaction time of the ego vehicle, comfortable braking deceleration, maximum braking deceleration, and the maximum braking deceleration of the cutting-in vehicle. A safety margin is included in the calculation of safe distances:

- **Value 0**: Achieved when the difference between the longitudinal distance and the safety margin exceeds the safe distance.
- **Value 1**: Achieved when the difference lies between zero and the unsafe distance (Mattas et al., 2022).

The Critical Fuzzy Surrogate Safety Metric (CFS) evaluates whether a scenario is critical:

- **Value 0**: Achieved when the longitudinal distance exceeds the safe distance.
- **Value 1**: Achieved when the longitudinal distance is less than the unsafe distance.

Safe and unsafe distances are calculated based on whether the expected speed of the ego vehicle after the reaction time is greater than or less than the speed of the cutting-in vehicle:

- If the expected speed of the ego vehicle is less than or equal to the cutting-in vehicle's speed, distances are calculated based on the ego vehicle's speed, the cutting-in vehicle's speed, and the current acceleration of the ego vehicle.
- Otherwise, distances are calculated using the ego vehicle's speed, its expected speed after the reaction time, the reaction time, the cutting-in vehicle's speed, and the ego vehicle's maximum braking deceleration (Mattas et al., 2022).

If the CFS value is non-zero, it is used as a factor for the difference between the maximum and comfortable braking deceleration. The resulting value is added to the comfortable braking deceleration. Otherwise, the PFS value is used as a factor for the comfortable braking deceleration (Mattas et al., 2022).

Table 3-5: Analysis Criteria for Fuzzy Safety Model (FSM) (Mattas et al., 2022)

Criterion	Description
Application Scope	The Fuzzy Safety Model (FSM) simulates a driver who employs defensive driving and early reactions to avoid critical situations. The goal is to derive performance requirements for AD regulation.
Modeling Approach	The FSM integrates fuzzy logic into the Surrogate Safety Metric (SSM) framework to assess longitudinal and lateral safety margins in real-time.
Definition of Human Reference	The FSM models a competent and cautious human driver.
Behavioral Coverage	The FSM covers distance regulation and braking maneuvers. The Critical Fuzzy Surrogate Safety Metric (CFS) component is specifically designed to react to unexpected events.
Scenario Coverage	The FSM is applicable to cut-in, cut-out, and car-following scenarios.
Modeled Influencing Factors	The FSM considers the comfortable braking deceleration as a driver related influencing factor.
Theoretical Basis	The model is based on fuzzy logic.
Parameterization	Mattas et al. (2022) use real world data, specifically the highD data to fix parameters. Details on how the parameters were derived are not presented. Parameters include reaction time, comfortable and maximum deceleration values, as well as the jerk, that describe human behavior in the specific scenarios.
Model Input and Output	Input are initial velocities and relative distances of ego and lead vehicle, both in longitudinal and lateral direction depending on the scenario. Output is the deceleration of the ego vehicle.
Validation	The FSM with different fuzzy safety metrics has been compared with data from the highD dataset.
Accessibility	The model structure and parameterization are available.

Driver Model by Jurecki et al.

The driver model proposed by Jurecki & Stańczyk (2009) aims to represent human behavior in pre-accident situations. While the authors did not originally intend for the model to serve as a reference driver model, it proves to be highly relevant for this purpose. The model incorporates both braking and steering components, as well as a decision-making process to determine the appropriate action in response to a critical situation that could lead to an accident.

At the core of the model lies the concept of *risk time*. Risk time refers to the interval between the moment a driver perceives an obstacle and the moment a collision with that obstacle would occur (Jurecki & Stańczyk, 2009). Through a series of experiments, the authors demonstrated that a driver’s decision-making process and responses, both braking and steering, are influenced by this risk time.

The braking behavior is modeled based on the relationship between the braking response, the relative lateral position of the vehicle and the obstacle, and the inverse of the risk time. Key factors influencing this behavior include the vehicle’s deceleration, the obstacle’s lateral position, the vehicle’s lateral position, and reaction times for braking. The coefficients of the model were calibrated through experimental studies.

Similarly, the steering input of the driver is modeled based on the difference between the lateral positions of the vehicle and the obstacle, along with the reaction time for steering. The turning angle at the wheels and the rate of change of this angle are influenced by these variables, and their relationships were also calibrated experimentally.

In addition to these dynamic responses, the model also considers the probabilities of different types of driver actions in critical situations. These actions include:

- steering,
- engine braking,
- regular braking.

The parameters for this driver model were derived from experimental studies conducted on a proving ground. During these studies, mock-up obstacles were revealed to drivers at varying distances and velocities to analyze their behavior. The specific parameter values and their derivation are detailed in (Jurecki & Stańczyk, 2009).

Table 3-6: Analysis Criteria for the driver model by (Jurecki & Stańczyk, 2009)

Criterion	**Description**
Application Scope	Representation of human behavior in crash or near crash situations.
Modeling Approach	Modeling of lateral and longitudinal control inputs with differential equations.
Definition of Human Reference	Average driver based on study participants.
Behavioral Coverage	Covers a steering and braking response.
Scenario Coverage	Covers only very specific scenarios with late reveal due to occlusion in an urban setting.
Modeled Influencing Factors	Modeled the risk time as the main influencing factor.
Theoretical Basis	The model is based on control theory
Parameterization	Parameters are directly extracted from a driving study. Conducted a driving study on a proving ground to replicate the scenarios that have been evaluated.
Model Input and Output	Input are relative distances and velocities between ego and the obstacle. Output are deceleration and wheel steering angle.
Validation	No study on plausability available.
Accessibility	Model structure is straightforward and available. Parameters are given.

The Non-Impaired Road User with their Eyes ON the Conflict (NIEON) model

The “Non-Impaired Road User with their Eyes ON the Conflict” (NIEON) model is a heuristic approach designed to model human reaction times in natural traffic situations. The focus of the model is to improve on the usually deterministic response timing of the reference model. The underlying principle of the model is the idea that drivers react differently depending on if they expect a stimulus or not. A simple example would be a scenario where the driver and his preceding vehicle approach a red traffic light. If the preceding vehicle slows down, this behavior is expected, so that the driver reacts differently than if the braking would be surprising. This means that the model assumes that reaction time depends on the current belief or assumption of the individual driver. The strong interdependence between reaction time, the situation, and the definition of the impulse has been a limiting factor in determining reaction times in traffic conflicts in previous models or assumptions. The NIEON model aims to address these limitations (Engström, Liu, et al., 2024).

To model reaction time, the NIEON model assumes that humans adjust their prior beliefs to posterior beliefs based on new evidence. The first key moment is when the initial *surprising evidence* of a conflict arises. The second key moment is when the posterior belief aligns with the evidence of the conflict. The time between these two moments is referred to as the *ramp-up time*. Reaction time is determined as the difference between the first moment and the moment of the first reaction (e.g., steering or braking) by the driver. These moments can be identified in naturalistic data, and the identified markers are then used in a linear model as a function of the *ramp-up time*.

If the driver has already started braking, the second moment is defined as the onset of stronger braking. Reaction time also includes the time required to physically move the foot to the brake pedal (Engström, Liu, et al., 2024).

The model is suitable for traffic conflict scenarios that require an immediate reaction. This suitability arises from the fact that the model involves a single *belief update* and execution of a maneuver requiring one step. For instance, Engström, Liu, et al. (2024) illustrate this with braking as an example maneuver.

The NIEON model has been extended with additional elements to address both braking, and steering (Scanlon et al., 2022). This allows the model to be used to simulate the trajectories of human drivers, without using other driver models.

Table 3-7: Analysis Criteria for the NIEON model

Criterion	**Description**
Application Scope	The NIEON model can be used to determine reaction times in traffic conflicts. Additionally, it can define the maximum latency of ADS, serving as a performance benchmark for evaluating ADS collision avoidance capabilities (Engström, Liu, et al., 2024).
Modeling Approach	The NIEON model is a heuristic model that captures the situational dependency of reaction times in traffic conflicts. It can be supplemented with machine learning techniques (Engström, Liu, et al., 2024).
Definition of Human Reference	The NIEON model simulates the dependency between reaction time and the scenario, assuming the driver is unimpaired and has their eyes on the conflict (Engström, Liu, et al., 2024).

Behavioral Coverage	The model represents an unimpaired driver focusing on the conflict, determining the situational reaction time (Engström, Liu, et al., 2024).
Scenario Coverage	Engström, Liu, et al. (2024) consider rear-end situations (collisions or near misses) where the driver is unimpaired and focused on the situation.
Modeled Influencing Factors	Influencing factors such as age, driving experience, distraction, cognitive load, fatigue or alertness can be modeled as influences on the speed of the belief updating process.
Theoretical Basis	The model considers deviations between actual and expected visual looming as the basis to determine the stimulus.
Parameterization	Engström, Liu, et al. (2024) manually identifies key timestamps and prior/posterior beliefs using video material from the Strategic Highway Research Program 2 (SHRP2). Similarly, (Scanlon et al., 2022) utilizes a manually curated database for various model parameters, determining values for actions like steering from naturalistic near-miss data. Scanlon et al. (2022) incorporates data from the Arizona Department of Transportation's publicly available crash database.
Model Input and Output	Inputs are initial hypothesis, alternative hypothesis, stimulus onset and stimulus end. The model also considers the initial state of the conflict scenario. Output is a single response time. The model has been additionally extended to include brake and steering reaction, in addition to the response timing.
Validation	The NIEON model's results were validated against driving simulator studies and values from existing literature. Validation showed that the model's values are consistent with those from comparable studies. Additionally, Scanlon et al. (2022) demonstrated that NIEON outperforms an average human driver in preventing collisions.
Accessibility	The model or parameterization have not been published.

3.5.3 Tactical decision models

Instead of reaction time models that are applicable in critical scenarios, tactical decision models can be used to define performance boundaries of human behavior to avoid conflicts before they become critical.

Active Inference Model

The Active Inference Model is an agent-based model that simulates the adaptive driving behavior of human drivers. It combines machine learning with a mechanistic model of human behavior, balancing goal-oriented and information-seeking driving behaviors (Engström, Wei, et al., 2024).

Goal-oriented driving is characterized by the pragmatic value, while *information-seeking driving* (e.g., checking the rearview mirror to avoid a conflict with a car in the adjacent lane during overtaking) is represented by the epistemic value. The epistemic value is maximized when observations deviate the most from prior assumptions, thereby eliminating uncertainties through these observations. The negative sum of these two values is referred to as the *expected free energy (EFE)*. The model determines control actions (e.g., steering) by selecting a sequence of future actions that minimize EFE. Action planning depends on the driver's assumptions, which are based on hidden states and the driver's preferences. Hidden states represent unobservable aspects of the environment, while preferences, defined as priors over observations, reflect the driver's goals, such as maintaining speed close to the speed limit. Hidden state assumptions are updated based on new observations (Engström, Wei, et al., 2024). A partially observable Markov decision process (POMDP) is used to represent the driver's generative model. The POMDP describes the evolution of hidden environment states over time. Since not all environmental states are observable, hypothetical states, such as a pedestrian hidden behind an object, are considered (Engström, Wei, et al., 2024).

Table 3-8: Analysis Criteria of the Active Inference Model (Engström, Wei, et al., 2024)

Criterion	**Description**
Application Scope	The Active Inference Model serves as a reference model for tactical decision-making in automated driving functions.
Modeling Approach	The Active Inference Model is a hybrid of machine learning and a mechanistic model of human behavior (Engström, Wei, et al., 2024).
Definition of Human Reference	The Active Inference Model models the adaptive driving behavior of humans, balancing goal-oriented and information-seeking driving strategies (Engström, Wei, et al., 2024).

Behavioral Coverage	The model includes lane keeping, distance regulation, braking, and acceleration maneuvers, which are part of goal-oriented driving. Additionally, it addresses uncertainty reduction through driving maneuvers, such as moving further left in the lane to minimize uncertainty about a potential hazard behind an object (Engström, Wei, et al., 2024).
Scenario Coverage	The model covers general scenarios involving tactical decisions, such as evasive maneuvers and managing visual distractions (Engström, Wei, et al., 2024)
Modeled Influencing Factors	The model can consider diverse driver preferences depending on use case. Some preferences used by the authors include deceleration comfort, preferred speed, comfortable accelerations, conflict avoidance and gaze preference, among others.
Theoretical Basis	The model is based on computational neuroscience (Engström, Wei, et al., 2024)
Parameterization	Engström, Wei, et al. (2024) do not specify a parameterization method. (Wei et al., 2022) uses factor analysis to determine parameter distributions derived from driving simulation experiments. Wei, McDonald, Garcia, et al. (2023) utilize the INTERACTION dataset to derive control inputs (e.g., accelerations).
Model Input and Output	Model input is an environmental model made up of states of different actors, which are composed from position, speed and acceleration. Model output are actions to be taken such as speed keeping, accelerating or lane changing.
Validation	Engström, Wei, et al. (2024) simulate two different scenarios (evasive maneuver and visual distraction) with varying parameter values and compares the results across both simulations. Wei et al. (2022) compares the model's outputs with data from the driving simulation. Wei, Garcia, et al. (2023) evaluate the model's results, particularly the final position of the vehicle, against a dataset. Wei, McDonald, Garcia, et al. (2023) compare the Active Inference Model with other models and dataset-derived parameters
Accessibility	The model or parameterization have not been published.

Driver models by Donà et al.

The aim of Donà et al. (2023) is to extend driver reference models from the longitudinal to the lateral domain. To achieve this, Donà et al. (2023) introduces two different steering models that can be used as references for automated driving functions: the purely kinematic model (K-LC) and the dynamical model (D-LC). In addition, both models are compared against a longitudinal reference model.

The K-LC model consists of symmetrical values for maximum and minimum lateral accelerations, as well as lateral jerk, to determine the steepness of the ramp-up and ramp-down of the lateral acceleration. The lateral movement is determined by integrating the resulting lateral acceleration twice. The benefit of this model lies in its computational efficiency, as it disregards all lateral vehicle dynamics. Compared to several other models, Donà et al., (2023) found that the K-LC model produces the shortest time required for a lane change when using comparable parameter values.

The D-LC model considers lateral vehicle dynamics based on the singletrack vehicle model. A minimum-time Optimal Control Problem (OCP) is solved to determine the minimum time for the lane change while applying constraints to disregard unrealistic trajectories (Donà et al., 2023). The same parameters for maximum lateral acceleration are used as in the K-LC model. However, due to the resource-intensive nature of solving the optimization problem, the D-LC model is not suitable for real-time applications. The authors primarily use this model to validate the more computationally efficient K-LC model.

Additionally, a braking reference model (K-BR) was proposed to compare against the lane change models. This model can also be used to determine a crossover velocity at which avoidance by steering is preferable to avoidance by braking. Its structure is very similar to that of other purely kinematic driver reference models.

Another approach for providing a reference in the lateral domain, as suggested by Wang et al. (2023), is to incorporate concepts from automated vehicle (AV) controller models, such as those developed by Park et al. (2021), Wurts et al. (2021), and Fehér et al. (2020), even though those models are not directly designed to replicate human behavior.

Table 3-9: Analysis Criteria for the driver models by (Donà et al., 2023)

Criterion	**Description**
Application Scope	Driver models as a reference for automated vehicles, especially for the lateral domain.
Modeling Approach	Both a kinematic and a dynamic model have been proposed.
Definition of Human Reference	Competent and careful human driver similar to (UNECE, 2021).
Behavioral Coverage	Lane changing and braking in separate models
Scenario Coverage	Lane change scenarios on highways.
Modeled Influencing Factors	Lateral displacement to avoid obstacle.
Theoretical Basis	The models are based on control theory.
Parameterization	Model parameters are derived from literature. Part of the dynamic model is an optimization for minimum time results. Model parameters are taken from Seiniger et al. (2013).
Model Input and Output	Specific model inputs are not discussed, but would need to be provided in such a way as to determine the point in time when the model activates. Model output is lateral acceleration.
Validation	The kinematic K-LC model is validated against the dynamic D-LC model.
Accessibility	The model equations and parameters are provided.

Careful and Competent Driver Model for Highway Merging (CCDM2)

The Careful and Competent Driver Model for Highway Merging (CCDM2) simulates a safe and competent driver for highway merging scenarios. The goal with CCDM2 is to provide a reference model for AV evaluation. To achieve this, the model is designed to emulate a skilled human driver to enable, especially in more challenging scenarios, to represent the human driving ability. The model tries to balance between overly risky and overly cautious behavior in order to create a benchmark that prevents reckless behavior of automated vehicles, while still not compromising their mobility (Wang, Guo, Zhao, et al., 2024).

The CCDM2 consists of two modules: the Model Predictive Control (MPC) module and the Monte Carlo Tree Search (MCTS) module. The MPC is a controller based on a two-wheel kinematic model with explicitly defined safety constraints.

The MCTS, a reinforcement learning approach, serves as the core decision-making framework of the model. A reward function prioritizing safety is implemented for the reinforcement learning process. MCTS penalizes trajectories that are time-consuming, uncomfortable, unstable, lack smooth curvature, or are unsafe. Unsafe trajectories are identified using the *time-integrated Time-to-Collision* (TIT) metric. The model offers three actions: *continue* (maintain the current lane), *lane change left* and *lane change right* (Wang, Guo, Zhao, et al., 2024).

The MCTS search process involves four stages:

- **Selection**: The process traverses the MCTS tree from the root using the *UCB1 selection policy*, balancing exploration and exploitation.
- **Expansion**: When a leaf node is reached, a random action is executed to expand the tree.
- **Simulation**: A Monte Carlo simulation is performed with a randomly selected action, determined by the current state and road network.
- **Backpropagation**: Once the termination conditions are met, the computed value is propagated back to the root, updating all nodes along the path.

During the MCTS simulation, the MPC determines the appropriate trajectory for the action selected by MCTS. Wang, Guo, Zhao, et al. (2024) CCDM2 combines the strengths of MCTS and MPC to emulate the decision-making and control capabilities of skilled human drivers. It tries to balance its output between safety, efficiency, and interpretability of the results.

Table 3-10: Analysis Criteria for the Careful and Competent Driver Model for Highway Merging (CCDM2) (Wang, Guo, Zhao, et al., 2024)

Criterion	**Description**
Application Scope	The CCDM2 model is designed for highway merging scenarios where the ego vehicle aims to enter the highway. It can serve as a safety analysis tool for automated vehicles.
Modeling Approach	The CCDM2 model consists of an interpretable reinforcement learning-based decision-making module, which is built on the interpretable Monte Carlo Tree Search (MCTS), and a safety constraint control module, which falls under Model Predictive Control (MPC).
Definition of Human Reference	The model represents a competent and safe driver, focusing on peak human performance rather than

	simulating an average driver (Wang, Guo, Zhao, et al., 2024).
Behavioral Coverage	The model includes the ability to perform lane changes required for merging onto the highway, as well as acceleration, steering maneuvers, and lane keeping. It aims to identify and execute safe and comfortable maneuvers. The focus is on lane change maneuvers.
Scenario Coverage	The model specifically addresses highway merging from onramps onto highways.
Modeled Influencing Factors	The model tries to target the optimal control output of the driver, without taking any factors that might reduce driver performance into account.
Theoretical Basis	Model Predictive Control is used for the theoretical basis.
Parameterization	For MCTS, a reward function is used to encourage or penalize various aspects of the maneuver, such as minimizing jerk. For MPC, a two-wheel kinematic model is employed to simulate the required vehicle dynamics. The ExitD dataset was used for parameterization. This dataset consists of drone-collected data focusing on highway on-ramp merging scenarios in Germany.
Model Input and Output	Inputs to the model are position, velocity and heading of actors in the environment. Model output are discrete actions like “continue” and “lane change”, as well as an optimal trajectory for each action choice.
Validation	Wang, Guo, Zhao, et al. (2024) validated CCDM2 by comparing it with the model proposed by Albrecht (2021) and realworld data from the exitD dataset.
Accessibility	Model structure and parameters are not available.

3.5.4 Data-driven models

Data-driven models incorporate real-world data with machine learning techniques to model driver behavior. They can be used to predict driver behavior in a variety of different driving situations but usually struggle with difficult edge cases (Da Lio et al., 2023).

Affordance Competition Hypothesis Model

The driver model proposed by (Da Lio et al., 2020) is designed to handle scenario edge cases that current automated vehicles struggle with. To achieve this, the authors introduce a model based on affordance competition in layered control architectures. The goal is to produce an agent that exhibits “polite” human-like behavior that emerges naturally from the model’s structure and is not deterministically programmed (Da Lio et al., 2023).

Broadly, the driver model tries to copy human cognitive processes, especially the action priming and action selection processes that are part of the Affordance Competition Hypothesis proposed by (Cisek, 2007). The selection is done in a competition process. Additionally, action biasing can be used to ensure compliance with traffic rules and norms. The selected action takes the form of a desired vehicle trajectory, which can then be analyzed using vehicle dynamics to produce the actual control inputs of the driver. The model is able to produce a wide range of behaviors, including both tactical decisions and low-level control inputs.

The actual action selection is based on the Multi-hypothesis Sequential Probability Ratio Test (MSPRT) algorithm (Da Lio et al., 2020). Actions are selected based on accumulated evidence over time. The benefit of using sequential testing is that the model can make decisions in real-time when enough evidence has accumulated. The model is also able to handle multiple affordances at the same time, which is a common scenario in driving.

Table 3-11: Analysis Criteria for Affordance Competition Model (Da Lio et al., 2023)

Criterion	**Description**
Application Scope	Driver model to handle complex edge cases.
Modeling Approach	Simulation of the human driver’s cognitive processes from the sensory cortex over the motor cortex to the motor output.
Definition of Human Reference	The reference for the model is a polite human driver.
Behavioral Coverage	The model handles both decisions, as well as longitudinal and lateral control.
Scenario Coverage	The model is not limited to certain scenarios.
Modeled Influencing Factors	The model uses a black-box approach without directly considering influencing factors.
Theoretical Basis	The model is based on affordance competition in layered control architectures.
Parameterization	Reinforcement learning is used to determine some parameters.
Model Input and Output	Model inputs are not described in detail. Model output is a selected action and corresponding trajectory.
Validation	There is no study on the model plausibility available.

Accessibility	Examples and simulation tools have been published as part of the Dreams4Cars project.

3.5.5 Agent models

Agent models are used to simulate all aspects of human driving behavior, including tactical decisions and low-level control inputs. They are designed to produce a wide range of behaviors and can be a collection of different models that are combined to simulate different parts of human driving behavior (Klimke et al., 2020).

RE:Sim

The RE:Sim model is a multi-agent framework designed to evaluate safety improvements enabled by automated vehicle technologies. It incorporates human states, such as distraction, to account for driving errors and can simulate various levels of automated driving (SAE Levels 1-4) (Kitajima et al., 2019). The source code for the model is publicly available at https: //github.com/Reisim, though this represents a limited version of the model used in (Kitajima et al., 2022). Kitajima et al. (2019, 2022) utilized the model to study rear-end collisions, head-on collisions, lane departure accidents, vehicle-pedestrian accidents, and “intersection V2V” scenarios.

The RE:Sim model combines road infrastructure data with agents representing vehicles, drivers, pedestrians, and their interactions. Parameters for driver behavior include observation/recognition, decision-making, and pedal/steering control (Kitajima et al., 2019). However, the exact implementation details of the algorithms are not specified by Kitajima et al. (2019, 2022). The model also incorporates parameters describing drivers, such as compliance with traffic rules, information processing capability, driving skills, and arousal level.

Human driving errors were derived from an annual report by the Japanese police, focusing on the five most common causes: inattention, aimless driving, insufficient safety checks, misjudgment, and improper operation. A separate framework models pedestrians, accounting for attributes such as gender and age (Kitajima et al., 2019).

For advanced driver assistance systems (ADAS) and automated driving, the following technologies were modeled:

- **Driver Assistance Systems:** Automated Emergency Braking (AEB) and Lane Departure Warning (LDW).
- **Level 2 Automation:** Adaptive Cruise Control (ACC) maintaining a Time Headway (THW) of 1.8 seconds.
- **Level 3 Automation:** An extension of the Level 2 system, augmented with a human trust metric for the system.

- **Level 4 Automation:** An ideal SAE Level 4 system with a sensor configuration specifying sensor types and their positions.

These implementations provide an evaluation framework for the safety impact of varying automation levels (Kitajima et al., 2019, 2022).

Table 3-12: Analysis Criteria of the RE:Sim Model

Criterion	**Description**
Application Scope	Evaluates safety improvements from automated vehicles, focusing on various accident scenarios such as rear-end, head-on, lane-departure, and pedestrian accidents (Kitajima et al., 2019, 2022).
Modeling Approach	A multi-agent model with representations for vehicles, drivers, and pedestrians. Drivers are modeled behaviorally, while vehicles and pedestrians include automation levels and walking speed distributions (Kitajima et al., 2019, 2022).
Definition of Human Reference	Represents diverse driver types, behaviors, and errors (Kitajima et al., 2019).
Behavioral Coverage	Includes algorithms for perception, decision-making, steering, and errors like inattention or misjudgment (Kitajima et al., 2019).
Scenario Coverage	Examines interactions among drivers, vehicles, and pedestrians, covering five accident types (Kitajima et al., 2019, 2022).
Modeled Influencing Factors	Factors include inattention, arousal, and information processing (Kitajima et al., 2019).
Theoretical Basis	Core model based on Wiedemann’s driver model. (Wiedemann, 1974)
Parameterization	Parameters derived from studies, experiments, and accident data. Driver assistance modeled per SAE levels (Kitajima et al., 2022).
Model Input and Output	Model inputs are states of actors and environment. Output is state of the ego vehicle at each timestep in the traffic simulation.
Validation	Simulated traffic densities compared with census data.
Accessibility	Source code publicly available and open-source.

GeoScenario Simulated Driver Vehicle (SDV) Model

The SDV (Simulated Driver-Vehicle) Model is a simulation framework designed to evaluate the behavior and decision-making of simulated road users in complex traffic scenarios in order to improve scenario-based testing of automated vehicles (Queiroz et al., 2024). It integrates individual vehicle planning processes with a centralized traffic simulation to create a dynamic and realistic environment. Each simulated road user is represented by an SDV Planner, which combines both driver and vehicle functions into a single entity. This abstraction simplifies the simulation by focusing on trajectory planning and execution rather than low-level driver inputs like steering or braking.

The SDV model operates through a two-way data-sharing mechanism. SDV Planners read the current traffic state (TS) and generate planned trajectories (TP), which the traffic simulation process uses to update the global traffic state. This interaction ensures a synchronized simulation.

Each SDV Planner follows a loop consisting of six steps: perceiving the surrounding traffic environment, predicting future traffic states, transforming these states into the Frenet reference frame aligned with lane geometry, executing a behavior tree to select maneuvers, planning precise trajectories for the chosen maneuver, and writing the updated traffic plan back to the system. The behavior trees are at the core of decision-making, with nodes representing conditions, maneuvers, or sub-trees, and operators coordinating their execution. These trees allow for dynamic responses to traffic conditions, enabling vehicles to handle tasks like lane changes, following other vehicles, or maintaining speed.

Trajectory planning is a critical component, beginning with target sampling to define potential end states for a maneuver. The system then generates smooth motion profiles using quintic polynomials, which ensure comfortable and realistic driving behaviors. An optimization step evaluates candidate trajectories against feasibility constraints, such as avoiding collisions, and cost functions, including minimizing jerk, maintaining efficiency, and adhering to scenario specific goals. The selected trajectory balances safety, comfort, and progress, aligning with the requirements of the scenario.

The Traffic Simulation component executes the planned trajectories at a high frequency, updating vehicle states in real time. This ensures seamless integration of individual vehicle actions into the overall traffic environment.

The SDV model is implemented through the open-source GeoScenario Server, which uses Lanelet2 maps and the GeoScenario language to define traffic scenarios. It integrates with simulators like WISE Sim. The architecture allows for customization, enabling integration with different simulation environments.

Table 3-13: Analysis Criteria for SDV (Queiroz et al., 2024)

Criterion	Description
Application Scope	Simulation of road user behavior in the context of scenario-based testing of automated vehicles.
Modeling Approach	Combination of a behavior tree and a trajectory planner.
Definition of Human Reference	No specific human reference is defined. The target of the model is a general human driver.
Behavioral Coverage	The model covers both decision making, as well as lateral and longitudinal control.
Scenario Coverage	The model is not limited to certain scenarios.
Modeled Influencing Factors	Influencing factors that lead to driver variability are not described.
Theoretical Basis	The model uses trajectory planning and a behavior tree to select maneuvers.
Parameterization	The model behavior can be adjusted by parameterizing the behavior tree. Additionally, parameters can be chosen for the trajectory planner, including time cost and efficiency cost, among others.
Model Input and Output	Model input are current traffic states, output is the vehicles trajectory.
Validation	No information on model validation is available.
Accessibility	The model source code and parameterization are not publicly available.

SimDriver

The SimDriver, an agent model developed by the Institute for Automotive Engineering at RWTH Aachen University (Becker et al., 2021), is designed to simulate responsive and human-like driving behavior in traffic scenarios. Capable of handling a variety of traffic maneuvers, it dynamically reacts to other traffic participants and is particularly suited for urban environments. The model supports integration through an Open Simulation Interface (OSI) adapter and a modular simulation architecture, enabling compatibility with simulation platforms such as CARLA.

The model is encapsulated as a *Functional Mock-up Unit* (FMU) using the *OSI Sensor Model Packaging* (OSMP) framework, ensuring interoperability with OSI-compliant platforms. It accepts environmental data and task-specific instructions as input, processes them through its internal behavior and vehicle dynamics models, and outputs the agent's updated state or desired control values. This modular design allows for either direct simulation of the agent's dynamics or the delegation of control to external modules.

The core behavior model processes input data through multiple layers. First, the *Perception Layer* acts as a pass-through interface, though it can be extended to simulate human-like perception errors. Next, the *Processing Layer* enriches the data with metrics such as *Timeto-Collision* (TTC) or *Time Headway* (THW) and selects the most suitable driving maneuver. These maneuvers are governed by conscious guiding variables, such as maintaining a safe headway, which are in turn controlled by subconscious outputs like acceleration and steering curvature. Finally, control signals are generated to execute the desired actions.

The agent is capable of performing a wide range of basic driving maneuvers through a state machine, enabling it to effectively handle acceleration, braking, lane following, and intersections. Parametrization options include setting the initial velocity and desired velocity directly within the FMU or adjusting other parameters via the source code.

For seamless integration, the model requires detailed input data from OSI fields, including information on vehicles, lanes, traffic signs, and lights. Supported actions include tasks such as following paths or adjusting speed. On the output side, the model provides precise updates for position, velocity, orientation, and desired dynamics, enabling further processing by the simulation platform.

Table 3-14: Analysis Criteria for the SimDriver

Criterion	**Description**
Application Scope	Agent model to replicate human behavior to aid in the development and testing of automated driving.
Modeling Approach	Different modules cover different aspects of driver behavior. Includes rule-set for decision making. Longitudinal behavior based on Intelligent Driver Model (IDM) (Treiber et al., 2000). Lateral behavior based on Two-Point Controller (Salvucci & Gray, 2004).
Definition of Human Reference	Replicates a general human driver.
Behavioral Coverage	Covers some tactical decisions, as well as lateral and longitudinal control.
Scenario Coverage	Diverse urban and highway scenarios.

Modeled Influencing Factors	Influencing factors not covered.
Theoretical Basis	The models different components are based on concepts from control theory.
Parameterization	Parameterization strategy using Genetic Algorithm (GA) available.
Model Input and Output	Input to the model are the Road Geometry and States of other agent in the simulation environment. Output of the model are desired acceleration and curvature. A separate component to translate into vehicle movements is available.
Validation	No studies on validation available.
Accessibility	Model source code is publicly available.

3.5.6 Cognitive models

Similar to agent models, cognitive models usually cover all aspects of human driving behavior. They are however, designed to simulate the cognitive processes of the human driver, allowing them to be applicable in a wide range of scenarios as long as the cognitive processes are similar (Siebke et al., 2022).

COSMODRIVE

COSMODRIVE (COgnitive Simulation MOdel of the DRIVEr) is a cognitive simulation model developed to replicate the processes involved in driving, including perception, cognition, decisionmaking, and action (Bellet et al., 2012). The model integrates theories from various fields, such as ergonomics, cognitive sciences, social psychology, and artificial intelligence, to simulate human driving behavior within a unified framework.

The driving activity in COSMODRIVE is conceptualized as a dynamic “Perception-Cognition-Action” regulation loop, encompassing both explicit (controlled and symbolic) and implicit (automatic and sub-symbolic) processes. The model incorporates two complementary perceptual processes: bottom-up integration of environmental information and a top-down active exploration. Additionally, it features a *virtual eye* that mimics drivers’ visual strategies based on empirical eye-tracking data (Bellet et al., 2012).

At the cognitive level, COSMODRIVE generates mental representations that act as simplified, functional models of reality. These are shaped by situational awareness, goals, experience, cognitive capacity, and attentional resources and inform risk assessment, decision-making, and action planning. Situational awareness, a key component in COSMODRIVE, is differentiated into two levels:

- *Attentional Level:* Controlled by the human driver, involving knowledge-based behaviors.
- *Automatic Level:* Operates in the background, handling skill-based behaviors.

Rule-based behaviors are situated between these two levels (Bellet et al., 2009). Situational awareness is achieved through mental representation elaboration based on driving schemas. Each driving schema aims to achieve a tactical goal and includes:

- A *Driving Path*: Represented as a sequence of different driving zones.
- A *Sequence of Actions*: Executed based on the presence and position of surrounding objects relative to the driver's vehicle.

The model's ability to represent risk awareness and surprise is particularly significant. Risk awareness is defined as the driver's recognition of a transition from a normal to a critical situation (Bellet et al., 2009). In COSMODRIVE, this is managed through the use of *envelope zones*, which define spatial boundaries around the driver's vehicle. These zones categorize other road users' proximity as either safe, a threat, or an immediate danger. Envelope zones are also used to anticipate the behavior of other vehicles (Bellet et al., 2012).

Beyond optimal driving performance, COSMODRIVE also simulates driving errors and challenges, such as the effects of prolonged visual distractions on situational awareness. Its development follows an iterative process combining ecological observations (e.g., real-world and simulated driving) with computational modeling of human cognition, including cognitive architecture, knowledge modeling, and algorithm development.

Table 3-15: Analysis Criteria for the COSMODRIVE Model (Bellet et al., 2012)

Criterion	**Description**
Application Scope	Holistic model of all cognitive processes of the human driver.
Modeling Approach	Modeling the cognitive process of the human driver in a perception, cognition and action loop.
Definition of Human Reference	The model tries to replicate behavior for a general human driver.
Behavioral Coverage	The model covers both the tactical, and the operational level, including the longitudinal domain using the envelope zones and the lateral domain using a pure-pursuit controller.
Scenario Coverage	No definite information on the scenario coverage is available. The model has been mostly evaluated for car-following scenarios in literature.

Modeled Influencing Factors	Modeled Influence Factors include risk, situational awareness and visual distractions.
Theoretical Basis	Modules of the model are based on different theoretical basis like ergonomics, cognitive sciences, social psychology, and artificial intelligence in general and Piagettian constructivism and the Neisser perceptual cycle specifically.
Parameterization	The parameterization methodology of COSMODRIVE is not detailed in literature.
Model Input and Output	Model inputs are the position of other objects in the environment, as well as the cognitive state of the driver. Model output is a vehicle trajectory.
Validation	The COSMODRIVE model has been validated against data from a custom simulator study (Bornard et al., 2016).
Accessibility	The model is not available publicly.

Stochastic Cognitive Model (SCM)

The Stochastic Cognitive Model (SCM) represents the cognitive and physical abilities and limitations of individual humans (Witt et al., 2019). It specifically focuses on modeling the cognitive processes of individuals (Witt et al., 2018). The SCM is used to simulate the behavior of road users (Fries & Fahrenkrog, 2021) and is divided into several submodules: *Information Acquisition*, *Mental Model*, *Decision Making Process*, *Action Implementation*, and *Driver Characteristics* (Witt et al., 2019).

The *Information Acquisition* module simulates the driver's perception of the environment and the current situation, with an emphasis on visual perception. This ensures that the model processes only the information visible to the driver (Witt et al., 2019). Gaze behavior and fixation durations are modeled as stochastic parameters (Fries & Fahrenkrog, 2021).

The *Mental Model* module describes microscopic traffic and extracts environmental information for the *Decision Making Process* module (Witt et al., 2019). Extracted data are stored within the Mental Model module, but these data can be incomplete or error-prone. Additionally, this module calculates the information required for determining necessary actions (Fries & Fahrenkrog, 2021).

The *Decision Making Process* module consists of two submodules: the *Situation Manager* and the *Action Manager*. It models the driver's decision-making process, incorporating stochastic variations when selecting the next action (Witt et al., 2019). Drivers can recognize and evaluate patterns in specific situations (Fries & Fahrenkrog, 2021). Finally, this module categorizes actions into primary driving actions (e.g., acceleration and steering) and secondary actions (e.g., turning on lights) (Witt et al., 2019).

Based on information from the preceding modules, the *Action Implementation* module adjusts the pedals and steering wheel. Another critical component is the *Driver Characteristics* module, which describes the driver's state, such as stress (Witt et al., 2019). This module influences all other modules within the model (Fries & Fahrenkrog, 2021).

Table 3-16: Analysis Criteria for the Stochastic Cognitive Model (SCM)

Criterion	**Description**
Application Scope	The SCM model aims to improve traffic simulation by modeling various drivers' perception, abilities, and individuality. This enables better prospective safety assessment of ADAS (Witt et al., 2019).
Modeling Approach	The SCM model comprises several modules describing the different subprocesses of driver decision-making. The Driver Characteristics module is probabilistically modeled, and the Decision Making Process incorporates stochastic variations for action selection. The model can be utilized in an agent-based simulation (Witt et al., 2019).
Definition of Human Reference	The SCM model represents various driver types, including their characteristics in perception and decision-making. This allows simulation of both average drivers and other specific driver profiles (Witt et al., 2019).
Behavioral Coverage	The SCM model captures diverse driver characteristics, including perception and decision-making processes. Decision making covers tasks such as lane keeping, following, lane changes, acceleration and deceleration, as well as their implementation with braking and steering inputs. Through modules like the information acquisition module, distractions or perception limitations can also be modeled (Witt et al., 2019).
Scenario Coverage	The SCM model covers exclusively highway scenarios, but is not restricted to specific driving situations, as it primarily describes human decision-making and can simulate various actions. Fries et al., (2022) applied the model to passive cut-in maneuvers as well.
Modeled Influencing Factors	The SCM model can incorporate various influencing factors and driver states, which may affect all or specific modules within the model (Witt et al., 2019).

Theoretical Basis	Several models, such as a model for vehicle guidance, are utilized to describe human behavior (Mai, 2017).
Parameterization	Witt et al. (2019) employed a driving simulator study for parameterization. While the parameter selection process was not specified, the considered parameters were detailed. To determine the correlation between driver characteristics and behavior, Witt et al. (2019) conducted a driving simulator (Hexapod) study.
Model Input and Output	Input to the model is the ground truth of the simulation environment. Model output is the vehicle trajectory.
Validation	Fries et al. (2022) compared the SCM model, simulated in an OpenPASS environment, with data from the highD dataset and the GIDAS PCM dataset
Accessibility	SCM has been made open source and is available to the public in its entirety. The model is not black box, so the model outputs can be traced throughout the model structure.

CogniBot Model

The CogniBot model is a cognitive behavior framework designed to aid in the development and testing of automated vehicles. The main novelty of the model is the integration of rule-based modeling with machine learning, reducing the number of parameters needed and significantly decreasing the training data requirements compared to purely data-driven models. (Brostek et al., 2024).

CogniBot organizes human behavior into three functional groups: *Perception, Cognition, and Action*. The *Perception* module simulates gaze control, attention, and visual perception, accounting for human limitations such as restricted fields of view, which are compensated by simulated eye movements. These movements are directed by both top-down signals (e.g., intended actions) and bottom-up stimuli (e.g., detecting traffic participants). The *Cognition* module creates an internal representation of the environment, which reflects recognized objects and incorporates uncertainties. Predictions about the behavior of other road users and scene classifications guide decision-making processes, which are also influenced by emotions, enabling the simulation of driver variability. The *Action* module handles decision-making, trajectory planning, and motor control. Decisions are governed by a cost function that optimizes trade-offs between speed, safety, and proximity to others, while motor control reflects individual differences such as age-related capabilities.

The CogniBot architecture is inherently stochastic, modeling perceptual inaccuracies and cognitive errors by adding noise to processed signals. For instance, the visual acuity decline in peripheral vision is replicated through probabilistic modeling. Scene classification and trajectory planning use compact neural networks, such as multi-layer perceptrons (MLPs) and long short-term memory (LSTM) networks, with significantly fewer parameters than traditional datadriven methods. This architecture ensures that the model can adapt to both standard and rare traffic scenarios without requiring extensive datasets.

The aim of the model is to incorporate collision avoidance and adherence to traffic rules based on rule-based driver models and data-driven components to replicate the full spectrum of human behavior in traffic. With the integration of rule-based components, the main downsite of data-driven models, that they require vast amounts of training data, particularly for rare events such as accidents, which can be limited. With approximately 100 free parameters derived from physiological and traffic research, the model requires vastly fewer parameters than comparable data-driven models (Brostek et al., 2024).

CogniBot’s capabilities were validated in public challenges such as the Waymo Open Sim Agent Challenge, where it demonstrated performance comparable to state-of-the-art data-driven models. The model enables realistic simulations of diverse traffic scenarios, including critical scenarios like accidents.

Table 3.17: Analysis Criteria for the CogniBot Model (Brostek et al., 2024)

Criterion	**Description**
Application Scope	Modeling human driving behavior for the development, testing, and validation of automated vehicles, including standard and rare traffic scenarios such as accidents.
Modeling Approach	Modular architecture with separate models for perception, cognition, and motor sub-processes. Combines rule-based methods with compact machine learning models for efficiency and realism.
Definition of Human Reference	Based on neurocognitive principles of human information processing, incorporating known limitations such as restricted fields of view and realistic reaction times.
Behavioral Coverage	Captures a wide range of driver behaviors, including decisions, as well as longitudinal and lateral control.
Scenario Coverage	Covers diverse traffic scenarios, including standard driving and rare critical events like accidents or near-misses.
Modeled Influencing Factors	Factors include visual perception, attention, cognitive decision-making, scene classification, trajectory planning, and motor control, as well as emotional states and physiological variations.

Theoretical Basis	Integrates rule-based approaches for structure and data-driven methods (e.g., MLP, LSTM) for adaptability. Emphasizes neurocognitive principles and stochastic processes to reflect human behavior.
Parameterization	Parameters are derived from physiological and behavioral research, traffic studies, and synthetic data generation for machine learning components.
Model Input and Output	Input to the model is the ground truth of the simulation environment. Model output is the vehicle trajectory.
Validation	Validated through public challenges such as the Waymo Open Sim Agent Challenge.
Accessibility	Detailed model information is not publicly available.

Driver Reaction Model (DReaM)

The Driver Reaction Model (DReaM) offers a method for validating ADAS or HAD functions in virtual environments, particularly for complex urban scenarios such as intersections. The model uses stochastic distributions to simulate realistic traffic scenarios involving numerous individual road users. DReaM is structured into four fundamental states: *Perception*, *Memory*, *Decision*, and *Action Implementation* (Siebke et al., 2022).

DReaM models both data-driven (bottom-up) and concept-driven (top-down) perception processes. Perceived information is stored in a *Cognitive Map*, which is limited by the constraints of working memory and includes a finite number of agent modules. At each time step, perceived information is saved in a data array. Reaction time is modeled by responding to information from *x* time steps earlier. Two types of reaction times are distinguished:

- *Initial reaction time*: Refers to the process when an event occurs for the first time. As the driver is unprepared for such events, the reaction time is extended.
- *Latency*: Represents periodic perception delays, such as when observing another vehicle (Siebke et al., 2022).

Kinematic information of agents not updated through gaze fixation is extrapolated based on the available data in the Cognitive Map. These interpreted data result in specific situational states, such as right of way, following another vehicle, collision with another agent, the current phase at an intersection, or imminent danger (e.g., a potential collision). These factors form an *attentional field* for the ego vehicle, which serves as the basis for decision-making (Siebke et al., 2022).

The decision-making process is divided into three stages: *Gaze Movement*, *Lateral Decision*, and *Longitudinal Decision*.

- *Gaze Movement*: Probabilities for bottom-up gaze movements are stored in a central "behavior configuration file." Top-down gaze movements depend on the current maneuver, intersection geometry, and situation. Fixation points include roadway areas leading to the intersection, corners where pedestrians and cyclists may cross, or other agents in imminent collision situations. If the ego vehicle is following another vehicle, this is also a fixation target.
- *Lateral Decision*: The model determines the current driving lane based on a computed graph representing the route to a destination. Routes are calculated at agent initialization using waypoints from an OpenSCENARIO file. If a lane change is required, an indicator is set, and lateral displacement to the new lane is calculated.
- *Longitudinal Decision*: The required acceleration to achieve the desired speed without colliding with other road users is calculated using the Intelligent Driver Model (IDM) (Siebke et al., 2022).

In the *Action Implementation* phase, lateral and longitudinal decisions are executed. At each time step, lateral displacement, including orientation errors relative to the reference line, is computed. The longitudinal acceleration is passed to the vehicle model, which limits acceleration according to physical constraints (Siebke et al., 2022).

DReaM is implemented in C++ and optimized for minimal runtime while maintaining sufficient accuracy. Its modular architecture positions it as a framework rather than a standalone driver behavior model (Siebke et al., 2022).

Table 3-18: Analysis Criteria of the Driver Reaction Model (DReaM)

Criterion	**Description**
Application Scope	DReaM validates ADAS and HAD functions in complex virtual scenarios like intersections (Siebke et al., 2022).
Modeling Approach	DReaM simulates driver behavior through cognitive processes and environmental interpretation. It comprises four components: Perception, Memory, Decision, and Action Implementation (Siebke et al., 2022).
Definition of Human Reference	The model is focused on accurately representing human variability. As such, different levels of human references can be achieved, depending on the choice of driver behavior parameters.
Behavioral Coverage	Models driver reactions such as perception delays and hazard fixation. Situational states include right of way, following, and danger. Fixation points focus on intersections, corners, or agents with collision risk (Siebke et al., 2022).

Scenario Coverage	Focuses on urban traffic and intersections (Siebke et al., 2022).
Modeled Influencing Factors	DReaM considers both different driver behavior parameters, driver states, and driver task demands as influencing factors to model driver variability.
Theoretical Basis	Implements UFOV for perceiving nearby vehicles' speed, position, and acceleration. Models both data- and knowledgedriven perception. Uses IDM for longitudinal decisions and a Stanley Controller for lateral steering (Siebke et al., 2022).
Parameterization	Parameters are adjusted via a central configuration file, with bottom-up processes calibrated through simulator studies (Siebke et al., 2022). Parameters are based on stochastic distributions (Siebke et al., 2022).
Model Input and Output	Input to the model are the ground truth of the simulation environment. Model output is the vehicle trajectory.
Validation	Demonstrated for evaluating ADAS and HAD with an Automated Emergency Braking system at intersections (Siebke et al., 2022).
Accessibility	Modular C++ framework with adjustable parameters via a configuration file (Siebke et al., 2022).

3.6 Comparison of reference models

When analyzing the different models we have presented for the safety assessment of automated vehicles, a series of commonalities and differences can be identified. Firstly, reference models have been proposed for a wide range of driver model categories, offering multiple ways to structure these models. For instance, one approach proposed by Wang, Guo, Yu, et al. (2024) is to distinguish models based on the type of avoidance behavior they consider. Wang, Guo, Yu, et al. (2024) categorize avoidance into braking, steering, and a combination of steering and braking.

Furthermore, additional types of avoidance behavior can be identified by introducing the level of tactical decision-making. For example, models like *Active Inference* focus exclusively on tactical decisions, while cognitive models that aim to holistically represent driver behavior encompass both tactical decision-making and avoidance through steering and braking. Additionally, some models do not simulate a complete avoidance process but focus solely on the driver's reaction timing. The categorization model types by their avoidance behavior is illustrated in Figure 3.1 with some model examples.

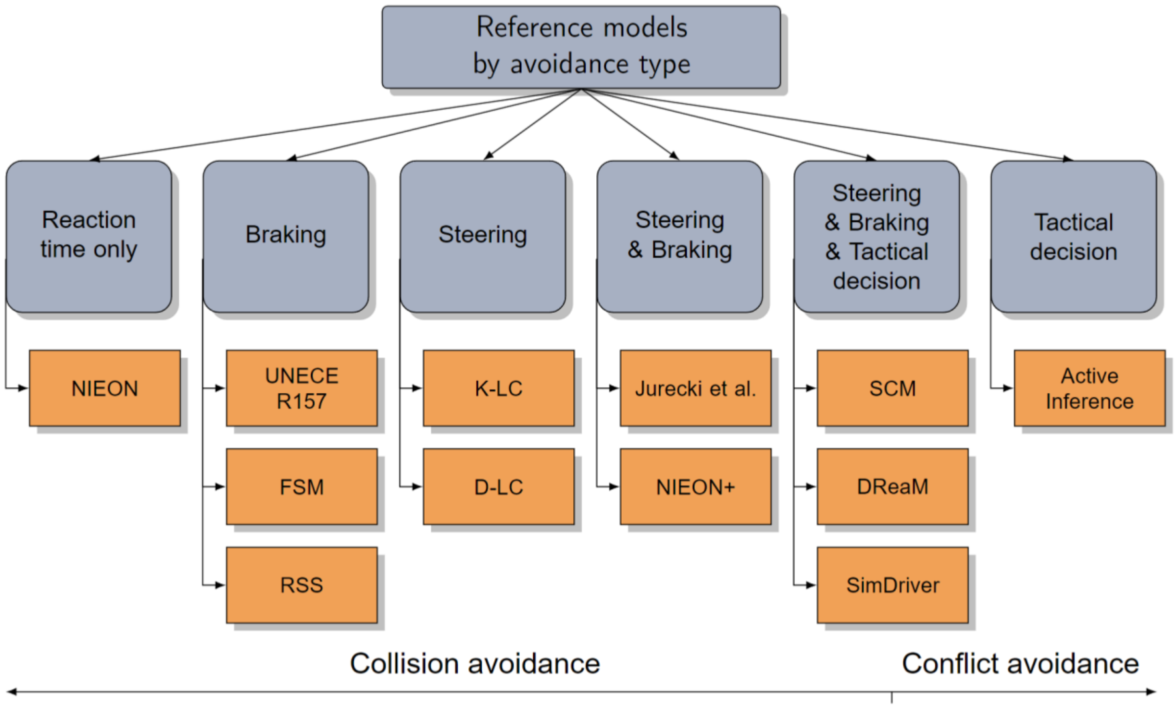

Figure 3.1: Categorization of reference models by avoidance behavior.

A distinction can be made between these models regarding their application and specific use cases in the safety assessment of automated vehicles. Broadly, we can categorize them into models focused on collision avoidance, conflict avoidance, or those addressing both. Collision avoidance models, for instance, can be simplified as they primarily consider reaction time, type, and severity. These models often address limited scenario types and specific avoidance behaviors, such as braking or steering. Consequently, their parameters are directly observable in studies designed to replicate the environments for which the models are valid. These models can then establish a minimum performance boundary for specific scenarios, which can then be used in the homologation process.

3.7 Research projects on reference models

Multiple research projects are ongoing to further categorize and develop driver models to aid in the safety evaluation of AD functions. Reference models have garnered significant attention in recent projects.

The *i4driving* project aims to develop a methodology to establish a credible and realistic human road safety baseline for the virtual assessment of Cooperative Connected and Automated Mobility (CCAM) systems (Nadi et al., 2023). This project considers driver models capable of simulating safety-critical driving behavior and heterogeneous human driving. A library of such models is being created, and the impact of human factors on driving behavior is studied. Methods to generate human factors data from studies, such as simulator studies, are also being developed (Nadi et al., 2023). The project is funded by the European Union and is ongoing until 2025.

The *V4SAFETY* project aims to develop a prospective safety assessment framework to evaluate diverse safety measures (Fahrenkrog et al., 2024). Part of this involves using driver models to create a baseline for assessment. The project provides an overview of the current state of driver models suitable for safety assessment and develops a categorization for these models, including driver reference models. The project is funded by the European Union and is ongoing until 2025.

The *BERTHA* project's main goal is to develop a scalable *Driver Behavioural Model* (DBM) based on probabilistic modeling, covering physical, cognitive, and emotional domains, including personal, cultural, and contextual factors (BERTHA project, 2024). Although the focus of the project deviates somewhat from using reference models for safety evaluation, the driver model in BERTHA is intended to enable the AD function to behave more human-like (BERTHA project, 2024). Nevertheless, the project covers several key aspects of driver models relevant to reference models, including data collection of human behavior, integrating this behavior into driver model development, and driver model validation (BERTHA project, 2024). The project is funded by the European Union.

4 Model parametrization and validation

“Although demonstrating a proposed controller in a simulated traffic environment is a necessary first step to show its potential, it does not provide sufficient evidence on how well the controller will generalize to real-world environments.” (Siebinga et al., 2022)

The validation of reference models is a crucial aspect of ensuring the validity of safety evaluations based on those models. As Markkula et al. (2012) state: *“The results of simulations will never be more valid than the models on which the simulations are based” (p. 1117)*. The validation process ensures that the model is able to predict real-world behavior accurately (Siebinga et al., 2022).

Siebinga et al. (2022) do however point out that a principled framework for such validation is still missing in literature. To address this gap, the authors propose a three-step validation workflow for driver models:

- *Select naturalistic data:* This step involves selecting a real-world dataset to compare against.
- *Tactical validation:* In this step, the model’s tactical behavior is validated against relevant extracted scenarios from the naturalistic data.
- *Operational validation:* This step involves validating the operational behavior of the model for each tactical behavior.

To validate the tactical level Siebinga et al. (2022) introduce the concept of tactical behavior categories that can be compared against the same tactical decisions in the naturalistic driving data. The validation of the operational level compares metrics that are representative for the tactical behavior under consideration. A simple example could be acceptable TTC during car following. The validation of the model should then both consider the validation on the tactical and operational level. While this process has not directly been designed for reference models, it is still highly relevant, as it covers driver models in general.

For the validation of reference models specifically, Olleja et al. (2024) compare the model outputs of several reference models including the CCDM and FSM discussed in Chapter 3 of this report in with SHRP2 data. The authors find that the models cause crashes in re-simulated scenarios that are not present in the SHRP2 data. Only a limited number of cases is used in their assessment. While in literature the term validation is used extensively, it is important to point out that the lack of appropriate data often makes a complete validation, where it has been shown conclusively that the model output matches the targeted reference, difficult. We propose that it is sensible to distinguish between a model validation and a model plausibility check. For ease of understanding, we will however use the term validation in this context as well.

An important consideration is the use of the correct type of data for the model or specific model behavior that is to be validated, since different data should be used to compare the model output against normal driving crash scenarios (Fries et al., 2022). More information is available in Section 4.1.4 on the data used. As a metric, Fries et al. (2022) propose the crash probability that is generated by the driver model for different concrete scenarios. Fries et al. (2023) also use field operational tests to compare against the SCM driver model in critical traffic scenarios. For more information on the data sources used for validation, see Section 4.1.

For parametrization, it is also relevant to consider the driver population targeted as the reference for the AD function. Filtering of input data according to driver characteristics and states is therefore an important step in addition to the match of input data to the targeted scenario characteristics, as also detailed in the examples provided below.

4.1 Overview on data sources

Chapter 2 provided a general overview on driving performance definitions, measures, influences and some considerations on different data types and data collection methods. It thus addresses available knowledge on driver performance as well as variability within driver populations that might be used to reduce information-related uncertainty in modeling applications (cf. Punzo & Montanino, 2020, for a review of uncertainty in model outputs and methods to reduce uncertainty). The analysis of the different performance models included an overview on parametrization and validation approaches. The focus of the following chapter is to provide a more general overview on data sources and data collection methods frequently referred to in driver modeling literature. A general comparison of methods for data collection or of parametrization and validation methods for models is not in the scope of this report. Rather, a general overview over frequently cited paradigms and examples for their application in the context of human performance modeling is pursued.

Generally, input for the parametrization of models or the plausibility of model outputs can be derived from statistics reported in publications (e.g., percentiles, mean values as for example in Engström, Liu, et al., 2024; Fries & Fahrenkrog, 2021) or from raw data of datasets or studies. Table 4-1 lists very general categories of input data covered by frequently employed data collection methods. Any finer differentiation between data types depends on the data collection equipment implemented for specific collection plans, such as:

- Are drivers’ gaze or body posture being tracked or are only descriptive meta-information on drivers included in the dataset (e.g., age, driving experience)?
- Is surrounding traffic captured and to which degree (e.g., type of vehicles or traffic participants, moving and static objects)?
- Which infrastructure elements are available as potential references for time- or distance-based metrics?

The following review therefore provides insights on exemplary data sets and how they have been used in the context of driver behavior modeling or as reference for AD functions.

Table 4-1: Overview on data categories generally covered by frequently cited paradigms of driver performance observation for parametrization or plausibility checks

Paradigm / Method	**General data categories covered**		
	Driver	**Vehicle**	**Environment**
Naturalistic driving studies (NDS)	✓	✓	✓
Driving simulator studies	✓	✓ (simulation output)	✓ (simulation output)
Drone data	✕	✓	✓
Crash databases	✓ (reconstructed)	✓ (reconstructed)	(✓) (limited reconstruction)

Other, less frequently found data collection methods found in literature include data gathered by event data recorders (EDR; e.g., Scanlon et al., 2015) or different forms of roadside units, e.g., Munich Motion Dataset of Naturalistic Driving (MONA; Gressenbuch et al., 2022). For other examples, see approaches such as camera data collected by Harth et al. (2022) at urban intersections or a study by Chae and Kim (2023) on modelling car following behavior. Next to driving simulator studies, controlled studies on closed tracks (e.g., Jurecki & Stanczyk, 2009) or laboratory studies implementing an abstracted driving task, for example using top-down views on the driving scenario (e.g., Siebinga et al., 2024), have been used to collect driver behavior for concrete scenarios. Next to parametrization purposes, Chandra et al. (2022) provide an example how video-based ratings of participants can be used to check the plausibility of classifications for risk-preference groups in traffic simulation. Regardless of the implemented experimental paradigm, controlled studies are often targeting selected challenging driving scenarios specifically tailored to the current parametrization or validation goal, i.e. merging or cut-in scenarios. Driving simulator studies offer the benefit of a reproducible implementation of complex environments for large samples and for placing drivers safely in urgent, challenging scenarios.

Relevant differentiation criteria between the data sources are the available level of detail on *driver-related data* (e.g., gaze data, driver states, driver characteristics) in addition to driver performance as observable from driver inputs, the analysis of trajectories or vehicle data. Further, *ecological validity*, i.e., the degree to which results generalize to the on-road setting for which human performance and AD functions are to be compared (cf. Green, 2000, for a discussion of ecological validity of different paradigms), is an important factor, as discussed below. A general issue remains the *accessibility of data*, especially from those paradigms feasible to provide data in safety-critical scenarios, as also concluded by Wang, Guo, Yu et al. (2024, p. 2377): “More open-sourced driver simulator datasets and crash datasets are desirable in comparison to the number of open-sourced naturalistic driving datasets”. While data on normal, non-critical driving with high ecological validity is more frequently captured and published, data on (near-)crash scenarios is less frequently captured in naturalistic setting and data from specific, controlled studies is even less often published apart from aggregated indicators (see Chapter 2 for input on performance indicators).

4.1.1 Naturalistic driving data

An extensive overview over different NDS and research using NDS data is provided in the review of Ahmed et al. (2022), in which 117 studies and six major NDS are considered. The review provides a detailed overview (measures, area of data collection, collection duration, scope, etc.) over selected large-scale NDS, including the 100-Car Naturalistic Driving Study, the Second Strategic Highway Research Program (SHRP2) and the Shanghai Naturalistic Driving Study (SH-NDS). The SHRP2 dataset (Hankey et al., 2016) is among the largest and – as also apparent from the analyses for this report – most frequently cited NDS.

Not all NDS referred to in the review by Ahmed et al. (2022) can be generally accessed to conduct further analyses. Another criterion to consider is the area where data collections took place. For example, Guo et al. (2022) report higher rates of safety-critical events in the SH-NDS, which uses the same data collection methods as SHRP2, and also consider differences in terms of distracted driving between Chinese and US drivers. Similarly, Saifuzzaman and Zheng (2014) state that "vehicular data used for calibrating and validating CF models were mostly collected in developed countries where drivers are generally less aggressive than their counterparts in developing countries. To capture the full spectrum of CF, it is desirable to use data containing more diverse driving behaviors, particularly more aggressive driving behavior" (p. 400).

With the availability of continuous and event-related vehicle, driver and environmental data as well as details on relevant driver characteristics (e.g., demographics, driver states, sensation seeking) and driver behavior (e.g., risky behavior such as cell phone usage, hand position), large-scale NDS provide valuable input for model parametrization. Examples include a predictive model for steering and braking avoidance based on 286 rear-end (near-)crashes of the SHRP2 dataset by Sarkar et al. (2021) or analyses of gap acceptance of Chinese drivers for 5608 cut-in maneuvers of the SH-NDS by Wang et al. (2019), who derived implications for simulation purposes from their analysis. Qi et al. (2021) derived car-following characteristics for AD functions from comparisons of the driving behavior of 53 drivers in Shanghai.

Olleja et al. (2024) aimed to validate the performance of the models described in R157 (UNECE, 2023) with human performance data. For this, 38 safety-critical cut-in near-crashes were extracted from the SHRP2 dataset and the scenarios were re-simulated with the reference models. The resulting trajectories could then be compared against the human performance data to evaluate if any crashes occurred (instead of the human-caused near-crashes). It was found that the reference models cause crashes in 9% of the cases where the human drivers did not crash. Additionally, the response of the reference models was delayed when compared with the original data. The authors conclude from their analyses that "the

CCDM model seems to be neither competent nor careful, while the FSM may be overly careful" (Olleja et al., 2024, p. 15).

Ahmed et al. (2022) state with regard to the parametrization of AD behavior: "In order to integrate the heterogeneous nature of human behavior through behavior cloning approach, real-time trajectory-level NDS data is essential" (p. 1). This appreciation of detailed, ecologically highly valid data can be considered to be equally true for the purpose of driver behavior modeling. However, as reviewed by Ahmed et al. (2022), NDS have several limitations, e.g. their explorative nature (as opposed to controlled studies) or the low number of recorded critical events. One additional aspect to consider in terms of data representativity might be that all NDS datasets reviewed by Ahmed et al. (2022) have been collected before 2018.

The effort to select relevant events for the current analysis purpose or to provide additional labelling to the large data basis should not be underestimated. The number of applicable events in the dataset can also decrease considerably based on the number of filter criteria including the targeted driver behavior such as eyes-on road (resulting, e.g., in 36 events for analysis out of 119 crashes and 3669 near-crashes of the incident type "rear-end, striking" in the SHRP2 dataset as reported in Engström, Liu, et al., 2024).

4.1.2 Driving simulator studies

Driving simulator studies have both been considered for parametrization as well as validation purposes in the context of driver performance modeling. Enabling a controlled experimental design to draw causal conclusions or the safe encounter of a diverse sample of drivers with safety-critical events are two general advantages. However, ecological validity needs to be considered within the current focus of research and the simulated environment.

Examples on how driving simulator studies can be designed to provide parametrization input for driver models are given by Witt et al. (2018, 2019). To provide sampling input to the SCM, participants were preselected to represent a balanced age distribution of drivers and the studies' ODD (highway driving) was selected with the SCM as the intended application case in mind. Other factors in the studies were varied systematically based on the investigated focus, e.g. traffic density or stress. Different driver characteristics were collected to investigate their impact on driver performance, especially on gaze behavior as one module of the SCM. Amongst other, "data underline the importance of considering gaze behavior and thereby information acquisition in the early stages of driver behavior models" (Witt et al., 2018). Other examples for parametrization data derived from specifically designed driving simulator studies can be found in Weber et al. (2023) for modeling collision avoidance at urban intersections and in Wei et al. (2022) for unexpected braking maneuvers.

Like the studies by Witt et al. focusing on the variability of driver behavior in the SCM, Itkonen et al. (2017) state more generally for CF models: "The validation of model parameters has typically been done by reference to an "average" driver. In recent years, interest in heterogeneous driver modelling has been increasing, with several studies addressing the problem” (Itkonen et al., 2017, p. 2). The authors report results of a driving simulator study (with N=15) conducted with the purpose of selecting measures for driving style classification in CF models.

Another example for the use of driving simulator data is the model developed by Engström, Liu, et al. (2024), which was parametrized by NDS data. Plausibility of model output was provided by comparison to average response times of four driving simulator studies conducted for similar scenarios that had been published prior. The prediction of the model for the single studies was considered acceptable, with a potential limitation for prediction quality being the restricted range of the available training data for the model from the SHRP2 dataset (see also a similar reasoning by Fries & Fahrenkrog, 2021, on other paradigms).

4.1.3 Drone data

Drone datasets provide the advantage of a bird’s eye view, allowing for the extraction of trajectory data in a naturalistic driving context with maximum ecological validity. The bird’s eye perspective, while limited to one data collection site and restricted to feasible weather conditions, provides the opportunity to collect data from all traffic participants within the area. However, no human factors data are included in these datasets, providing no direct input for parametrization of modules related to, e.g., driver states or gaze behavior. Similar as with NDS, the occurrence of safety-critical events is rare. The following table provides an overview on datasets and the included road type and road users. The table focusses on datasets available for non-commercial use. Licensing for commercial use of some of these and further datasets is also available, e.g. via leveLXData (http://levelxdata.com).

Table 4-2: Overview on selected drone datasets with a focus on availability for non-commercial use including reference links or publications for further descriptions

Name	Area	Road type / Scenario	Scope
highD (Krajewski, Bock, Kloeker & Eckstein, 2018)	Germany (6 locations)	Highways • Free Driving *(Longitudinal uninfluenced driving)* • Vehicle Following *(Longitudinal influenced driving)* • Critical Maneuver *(Low TTC or THW)* • Lane Change (https://levelxdata.com/highd-dataset/)	• 110500 vehicles • 44500 driven kilometers • 147 driven hours
inD (Bock, Krajewksi, Moers, Runde,	Germany (4 locations)	Urban – Intersections (https://levelxdata.com/ind-dataset/)	• 8200 vehicles (car, truck/bus) • 5300 vulnerable road users (pedestrian, bicyclist)

Vater & Eckstein, 2020)			
exiD (Moers, Vater, Krajewski, Bock, Zlocki & Eckstein, 2022)	Germany (7 locations)	Highway entries and exits • Free flow • Traffic jam • Slow traffic • On/Off ramp and merging Additional details • Lane identifiers • Surrounding vehicles, • KPIs such as TTC and THW • Lane coordinate data (https://levelxdata.com/exid-dataset/)	27300 driven kilometers 69430 road users: • Car • Van • Pickup • Truck • Bus • Motorcycle
rounD (Krajewski, Moers, Bock, Vater, & Eckstein, 2020)	Germany (3 locations)	Urban Variety of roundabouts with different speed limits (https://levelxdata.com/round-dataset/)	13740 road users: • Car • Van • Trailer • Truck • Bus • Motorcycle • Bicycle • Pedestrian
uniD (leveLXData, 2021)	Germany (1 location)	Urban – the University Drone Dataset (https://levelxdata.com/unid-dataset)	• 1380 vehicles (car, truck/bus) • 8600 vulnerable road users (pedestrian, bicyclist)
Waterloo multi-agent traffic dataset	Canada	Intersection and Crosswalk (https://uwaterloo.ca/waterloo-intelligent-systems-engineering-lab/datasets)	1 hour recording each Classes of road users: • Car • Pedestrian • Medium / Heavy vehicle • Bicycle • Bus
Interaction (Zhan et al., 2019)	Multiple	Highway and Urban • Roundabout • Unsignalized intersections • Signalized intersections • Merging and lane change (https://interaction-dataset.com/)	Roundabout • 10479 vehicles • 365 min video recording Unsignalized intersections • 14867 vehicles • 433 min video recording Signalized intersections • 3775 vehicles • 60 min video recording Merging and lane change • 10933 vehicles • 132 min video recording
SinD (Xu et al., 2022)	China	Urban Signalized intersection	7 hours of recording 13000 traffic participants: • Car • Bus / Truck • Motorcycle • Bicycle / Tricycle

		(https://github.com/SOTIF-AVLab/SinD)	• Pedestrian

pNEUMA
 	
(Barmpounakis & Geroliminis, 2020)
	Athen	Urban
		
		100+ intersections
		
		(https://open-traffic.epfl.ch/)
			• Five flight sessions of 2.5h per day (8:00-10:30)
			• 1.3 km² area with more than 100 km-lanes of road network
			• 500000 vehicles:
			  • Car / Taxi
			  • Bus
			  • Medium / Heavy vehicle
			  • Motorcycle

One example for using drone datasets to provide plausibility for the model output is given by Fries and Fahrenkrog (2021; see also Fries et al., 2022). The authors focused on the question if real world traffic is correctly represented by the simulated traffic. Results of endurance simulations were compared to field operational data (e.g., euroFOT) and the highD dataset, finding an overall good correspondence in following behavior as operationalized by frequencies of THW values. For higher THW values, observed discrepancies between simulated data and real-world data are explained with limited sensor ranges in FOTs as well as the data collection method for drone data (both leading to range restrictions in THW values).

As another example, Wei et al. (2023) used extractions from the INTERACTION dataset to parametrize and evaluate the outcome of different modelling approaches (i.e., intelligent driver model, behavior cloning, active interference driving agent). Evaluation was done with two separate subsets of data to analyze whether the models could generalize to new (i.e., unseen) vehicles in the same as well as in novel traffic conditions. A similar comparison of classifications by different models (i.e., models presented as part of the UN Regulation 157, the RSS model and the FSM model) was conducted by Mattas et al. (2022) with a subset of cut-in cases extracted from the highD dataset. The expectation was that each model should correctly classify these cases as preventable, as no collisions were included in the comparison data. Wang, Guo, Zhao et al. (2024) extracted challenging merging interactions from the exiD dataset (based on longitudinal distances) with the aim to select a human performance reference exhibiting drivers' peak performance. An additional example using the inD dataset for parametrization of a model can be found in Ziegler et al. (2022).

4.1.4 Crash data

Another data source, addressing the lack of non-successful real-world data, are reconstructed accident data. One example for such a dataset is the German In-Depth Accident Study (GIDAS; https://www.gidas.org/). Accidents are documented by interdisciplinary teams at three locations in Germany (Dresden, Munich and Hannover). Over 3000 individual data points are coded per accident and about 2000 accidents are recorded each year.

These efforts illustrate a point also made by Bärgman et al. (2024) as motivation for an approach to generate synthetic, realistic baseline scenarios for rear-end crashes (based on the CBM, as detailed in Chapter 2.2):

> *"There are several reasons why synthetic baseline generation is more enticing than using actual crash data. Firstly, crashes are rare, which means that the statistical power of an assessment that only uses actual crashes is often limited. Secondly, collecting data from actual crashes is very costly. Creating synthetic crashes in a virtual environment is likely to be substantially cheaper. Thirdly, crash data represent the crashes of "yesterday"; they are not necessarily representative of the crashes of today or the future." (p. 375)*

An example for how data from reconstructed crashes (GIDAS pre-crash matrix (PCM)) can be used in the modeling context is given by Fries et al. (2022) for an evaluation of SCM performance. Fries et al. contrast collision-free driving data in the highD dataset with crash cases from GIDAS PCM to compare the collision risk resulting from openPASS simulations with real-world data for a passive cut-in scenario. The number of crashes available for analysis in the specified evaluation area (defined by distances between vehicles and relative velocities at the start of the lane change) is rather small with only eight documented crashes. In comparison, the number of uneventful cut-in maneuvers with the same starting conditions from the drone dataset is much larger (N=371), illustrating the difficulty of gathering a sufficient data basis of non-successful interactions for comparison of model performance.

Although crashes are rare events, this mismatch in numbers might also be partly due to the "selection bias" (Bärgman et al., 2024, p. 376) of crash databases, although different databases apply different criteria:

> "*Basically, all crash databases censor lower-severity crashes for failing to meet some inclusion criteria. For example, they might only include crashes when someone is injured (e.g., German In Depth Accident Study; GIDAS; Schubert et al., 2013), when repair costs are greater than a given threshold (Isaksson-Hellman & Norin, 2005; Ydenius, Stigson, Kullgren, & Sunnevång, 2013), or when a vehicle has to be towed from the scene (US-DOT, 1998). In any case, censored crashes will not be in the database*." (p. 376)

Bärgman et al. (2024) compared the output of their crash-causation model, incorporating four main reasons for rear-end crashes (i.e., the CBM), to reconstructed crash data from the GIDAS database, including compensation mechanisms for different crash severity levels included in the synthetic and real-world data for comparisons. The implications of using different parametrization data (in this case for off-road glance behavior) are discussed in terms of the achieved fit between real-world and simulated data as well as limitations due to lack of knowledge, e.g. on frequencies of the different crash-causation mechanisms.

Another example for comparison data retrieved from reconstructed crashes is provided by Scanlon et al. (2021), who requested data from the Arizona Department of Transportation to answer the question how well their ADS would have performed within the same fatal conditions. The material included EDR reports as well as witness statements and scene diagrams, although the availability of materials varied between cases. Reconstructions included pre-crash kinematics of each actor either involved or relevant for the crash, dimensions and properties of actors and objects as well as traffic signal information.

4.2 Summary of findings on parametrization and validation

Different paradigms have been considered in the literature as input for model parametrization and for plausibility checks. Generally, validation efforts for most available models are currently not considered to be sufficient (Olleja et al., 2024).

As reviewed, available data sources differ in terms of data format and types (e.g., aggregated metrics, driver characteristics), their accessibility, ecological validity and the inclusion of traffic conflicts. Especially the latter aspect in combination with data access could present a challenge for plausibility checks and parametrization data, although some methodological approaches have been reviewed. In comparison, normal driving behavior can be derived from multiple data sources. However, depending on the targeted driver behavior, further work is necessary to extract or label relevant aspects before use of the data.

For reference purposes, ecological validity should be considered closely both for parametrization as well as for validation. The low number of (near-)crash situations captured in naturalistic settings is often countered by controlled studies for specific scenarios on closed-tracks, in driving simulators or in laboratory settings. Further, the applicability of the driver characteristics included in the data basis has to be considered. As discussed, available datasets might not represent all kinds of relevant driving styles, driver types or traffic cultures (e.g., Saifuzzaman & Zheng, 2014).

5 Identified research gap

The goal of this report is to provide a review on driver performance models as references for AD functions, emphasizing their role in providing a human-centric benchmark for evaluating system capabilities. By grounding model output in human driving performance, it becomes possible to assess how well automated systems align with or exceed human performance.

The reviewed literature highlights the complexity of human driving, focusing on perception, response to stimuli, and factors like attention and fatigue. Driver models vary from reaction-based models, common for regulative purposes, to cognitive models that simulate full decision-making processes, including driver errors. The latter aim to reflect diverse human performance and provide benchmarks for scenarios such as lane changes and emergency reactions.

However, most models lack a robust validation due to insufficient output comparisons to relevant performance or real-world data. Addressing this issue requires the availability of diverse datasets, including naturalistic driving studies, drone traffic observations, and customizable study results for challenging scenarios (e.g., driving simulator studies). This represents a critical shortfall, as the safety evaluations derived from these models are only as reliable as the models themselves.

To address these challenges, we propose creating a representative sample of highway driving scenarios to rigorously test various reference models. The highway domain allows for a clear definition of scenarios that occur in the system's ODD. This can then be followed up by looking at other more challenging domains as well, like urban traffic. Ensuring the plausibility of these models requires integrating diverse driving data, encompassing both normal driving situations and critical scenarios, including accidents. By mapping this data alongside the models' predictions, we can enable a robust evaluation of their ability to predict driver behavior accurately. For each scenario, a defined parameter space may serve as the basis for model evaluation. Within this parameter space, each model spans a subspace representing its performance boundaries. This subspace identifies specific concrete driving scenarios where the reference model fails to avoid a collision. Analyzing these sub-spaces across different reference models allows us to compare their performance requirements and highlight their respective strengths and weaknesses.

To enhance the evaluation, additional parameter sub-spaces can be derived using a variety of driving data sources. Normal driving data, such as drone datasets or infrastructure recordings, ensures that collisions predicted by the model do not overlap with normal driving situations. Critical incident data, such as from the GIDAS database, offers an additional layer of validation by testing models against accident scenarios. This approach provides a more comprehensive assessment of the model's ability to predict realistic driver behavior.

A particularly challenging region within the parameter space is the transition between normal driving and challenging situations. These scenarios are rare in everyday traffic and do not always result in recorded accidents, making them difficult to capture in datasets. A similar assessment has already been performed by Fries et al. (2022) for the SCM model specifically.

To address the gap in data availability, driving simulator studies for defined scenarios offer a viable solution. Simulators can generate controlled starting conditions for a driver sample specifically targeting the transition region between normal driving and critical situations. This approach allows us to evaluate model performance in this area, determining which reference models can predict driver behavior effectively across the entire spectrum of driving scenarios.

In general, we can see that relevant data sources for the development of reference models are still limited. Further activities should focus on the collection and (open source) publication of diverse data to ensure that the models can be developed and validated for a wide range of driving scenarios. This will help to ensure that the models are robust, reliable, and applicable to a wider range of driving scenarios.

Additionally, we see a lack of models that consider tactical decisions for conflict avoidance, similar to those proposed by Engström, Wei et al. (2024). The research in this area has focused heavily on a few scenario types, such as lane-changing, as seen in Wang, Guo, Zhao et al. (2024) or Donà et al. (2023). The tactical behavior of human drivers includes many more aspects, which leaves the possibility to further explore this area and to extend model coverage for reference models even further.

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