**TECHNISCHE UNIVERSITÄT MÜNCHEN**
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# Modeling of Take-Over Performance in Highly Automated Vehicle Guidance

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# Abstract

Highly automated driving is currently being widely discussed and likely to enter series vehicles within the next few decades. While the system takes over longitudinal and lateral control, the driver is still needed as a fall-back level in case system limits emerge. In those situations, the system prompts a take-over request, and the driver has to regain vehicle control within a limited time budget. These take-over situations will be one key controllability aspect of future highly automated vehicles, while a change of paradigms due to the automation of the driving task challenges traditional controllability methods. An approach to model drivers' performance is proposed in this thesis to address the changed demands on methods and provide a basis for the evaluation of the take-over situations in highly automated vehicles.

By conducting six driving simulator experiments, different parameters were identified which influence drivers' take-over performance, and the take-over performance was modeled under consideration of these different identified predictors, namely the available time budget, the current lane, surrounding traffic density, number of previously experienced take-overs, driver's load, eyes-off-road and age.

Among the different model approaches that were compared, regression methods showed the best combination of accuracy with simultaneous transparency regarding the influence of each predictor, as well as the interaction between the predictors. In total, 753 recorded take-overs served as a database for setting up regression models, depicting gaze reaction time, take-over time, maximum lateral and longitudinal accelerations, brake and crash probabilities and minimum time to collision. As the maneuver type significantly influenced the models' prediction, separate regressions for braking and non-braking drivers were set up and robust regression methods were used to address the occurrence of outliers in the data.

The different regression models' adequacy was assessed to be accurate with limitations when modeling brake reactions. The models proposed were validated by a comparison to results of a new driving simulator experiment and also by contrasting the models' predictions with results of four experiments of other authors. Results of these experiments were precisely predicted by the models in most of the cases, which confirmed models' accuracy and a high range of validity.

Traffic density, the time budget available for taking over vehicle control, the repetition (training), and driver's age played a major role when modeling take-over performance, whereas driver's load due to non-driving-related tasks had an rather low effect. The established models of human performance fit the behavior of drivers in take-over situations. Learning effects, for instance, were present and followed a logarithmic trend. Additionally, by employing mixed-effect models, the driver was recognized to be a major source of variance within the data, which is why knowledge of drivers' strategies and predisposition significantly improves the accuracy of the predictions.

The thesis makes it possible to predict and substitute driving simulator experiments. It provides an in-depth understanding of interdependency and importance of the different predictors and facilitates the controllability assessment of highly automated vehicles.

# Acronyms

| | |
|---|---|
| ABS | Anti-lock Braking System. |
| ACC | Adaptive Cruise Control. |
| ADAS | Advanced Driver Assistance Systems. |
| AEB | Advanced Emergency Braking Systems. |
| ANN | Artificial Neural Network. |
| AUC | Area Under the Curve. |
| BASt | Bundesanstalt für Straßenwesen. |
| DARPA | Defense Advanced Research Projects Agency. |
| DGPS | Differential Global Positioning System. |
| ESC | Electronic Stability Control. |
| ESP | Electronic Stability Program. |
| GPS | Global Positioning System. |
| HAD | Highly Automated Driving. |
| HAV | Highly Automated Vehicle. |
| HMI | Human Machine Interface. |
| LIDAR | Laser Illuminated Detection And Ranging. |
| LKAS | Lane Keeping Assistant Systems. |
| LRR | Long Range Radar. |
| LVS | Lead Vehicle Stationary. |
| NHTSA | National Highway Traffic Safety Administration. |
| OEM | Original Equipment Manufacturers. |
| OLS | Ordinary Least Squares. |
| RMSE | Root-Mean-Square Error. |
| ROC | Receiver Operator Characteristic. |
| SAE | Society of Automotive Engineers. |
| SD | Standard Deviation. |
| SRR | Short Range Radar. |
| STDLP | Standard Deviation of Lateral Position. |
| SuRT | Surrogate Reference Task. |
| TB | Time Budget. |
| TJA | Traffic Jam Assist. |
| TOR | Take-Over Request. |
| TTC | Time To Collision. |
| V2X | Vehicle-to-X communication. |
| VIF | Variance Inflation Factor. |

# Definitions

**Take-Over:**

Transition from higher levels of automated vehicle guidance to manual or assisted driving by reallocating control of the driving task back to the driver.

**Automation Scenario:**

Environmental conditions that allow the usage of the automated system.

**Take-Over Situation:**

Temporary and localized conditions among which a take-over is conducted.

**Take-Over Scenario:**

Environmental conditions among which a take-over is conducted.

**System Limit:**

Summary of situational conditions that cause the necessity of a take-over or triggers a minimal risk maneuver.

**Take-Over Request:**

Information of stimulative nature, emitted by the automated vehicle with the purpose of initiating a take-over.

**Time Budget:**

Time provided for the take-over and the execution of a maneuver, as an adequate response to the system limit.

**Take-Over Performance:**

Combination of timing and quality aspects of driver's input within a take-over scenario.

# Contents

# 1 Introduction

Within the last few years, automated driving has evolved as one of the most widely discussed topics in road transportation research. Thanks to advances in sensor technology and by merging data from sensors currently used for Advanced Driver Assistance Systems (ADAS), automatization of several parts of the driving task was enabled. Due to this progress, Highly Automated Driving (HAD) became a realistic vision for the near future. Proponents expect vehicle automation to have a positive impact, such as improved traffic flow, a reduced accident rate and a reduction of fuel consumption. Those aspects will only take effect if the automation is designed appropriately, utilized and accepted by the potential target group and the surrounding traffic. In order to address this coherence, the driver has to be considered within a system that covers not only the properties of the automation, but also the vehicle and the environmental conditions. Automation-induced changes of driver's behavior and performance must be considered as well as the change of demands on the driver's abilities such as staying vigilant or taking over control after driving in automated mode. Automated systems that take over parts of the driving task are already entering the market, but currently requiring the driver to continuously monitor the system. It is estimated that highly automated systems which do not have to be monitored constantly will emerge within the next decade (Schreiner, 2014).

In this setting, the driver is no longer in charge of executing longitudinal or lateral control, but remains the fallback level of the automation in case of system limits or when the end of the automation scenario is approached. The task, then, has to be reallocated to the driver - he has to take over vehicle control. In the same way that the automation must perform accurately and flawlessly, the evaluation of drivers' behavior and performance interacting with the system in such take-over scenarios is an essential requirement to enable automated driving in series vehicles and ensure traffic safety. This includes a profound understanding of the effects that arise when humans are exposed to vehicle automation. The examination of the interaction of driver, vehicle and automation in specific circumstance, for example in critical take-over scenarios, is an inevitable research focus and required for the discussion of ethical, legal, liability, insurance and especially safety aspects.

At the same time, the current state of knowledge is very limited and huge efforts in the form of driving simulator experiments, on-track driving experiments and naturalistic driving studies have to be undertaken to provide a sufficient knowledge base for the controllability assessment of highly automated vehicles. This traditional approach of controllability assessment is likely to be insufficient and not practical considering the extent of studies necessary. In this context, the ability to model the driver-vehicle-automation system would be very advantageous. By modeling the impact of automated driving on drivers' behavior and driving performance, elaborate experiments can be substituted and coherence can be discovered that otherwise could hardly be derived from isolated experiments. Therefore, this thesis focuses on modeling take-over performance, based on a series of driving simulator studies, in dependence on different influencing preconditions.

# 2 Automation in Vehicle Guidance

## 2.1 Vehicle Guidance

When driving, the main goal is to cover the distance to a destination by the use of a vehicle and with the constraints of avoiding harm to the passengers, other road users and objects. There may also be other subordinate goals such as minimization of fuel consumption or maximization of joy. In order to achieve these goals, the driver has the possibility to make different inputs on the control elements, such as steering, braking, accelerating and operating other functions like headlights or wipers. The former are parts of the primary driving task, whereas operating functions necessary for driving but not directly correlated to vehicle guidance are secondary driving tasks (Geiser, 1985). The third group of driving tasks, the tertiary driving tasks, are all operations serving to maximize comfort or joy, for example adjustments on the air conditioning, windows or radio (Geiser, 1985; Bubb, 2015b). Figure 2.1 summarizes the different tasks.

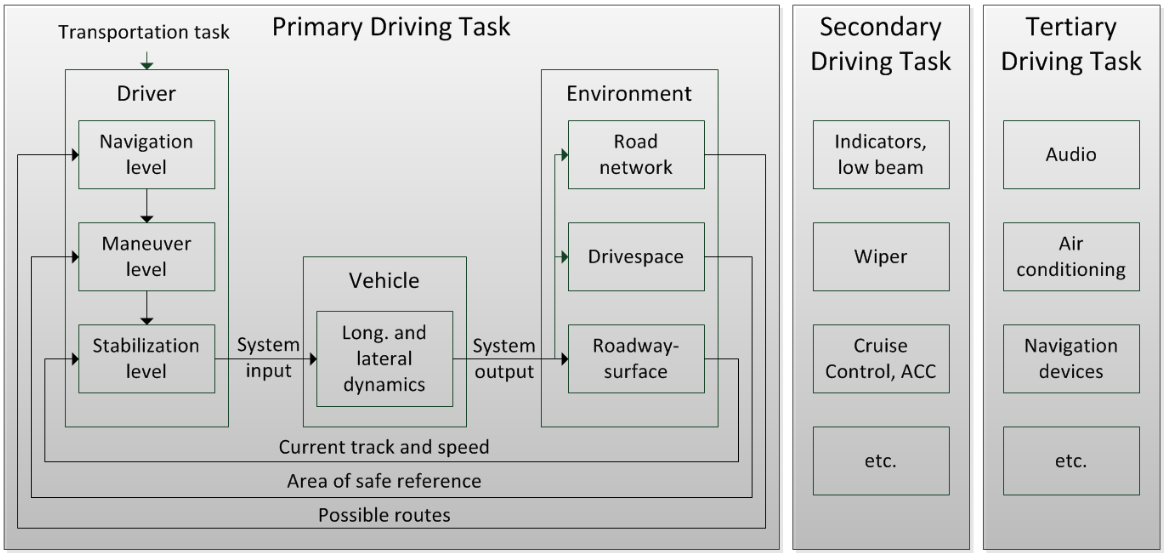



Figure 2.1: Levels of vehicle guidance and subdivision of the driving task. Derived from Donges (1982) and Negele (2007).

With respect to automating the driving tasks, focus is clearly on the primary driving task. Secondary or tertiary tasks can also be the target of automatization, however, in general and in this thesis specifically, solely the automation of the primary driving task is attributed to “automated driving”. This primary driving task can further be subdivided into three different levels (cf. Figure 2.1), probably originating from the aviation domain and widely used in road transportation (Crossman & Szostak, 1968; Bernotat, 1970; Donges, 1982). On the highest level, the driver plans aspects for navigation considering different routes to the destination in dependence of influencing factors such as the current traffic situation. The second level represents the maneuvering of the vehicle, including lane-changes, turns, passing and others. The third level describes all actions necessary to stabilize the vehicle within the current lane (lateral) and concerning vehicle speed (longitudinal).

The driver can therefore be considered a controller within a closed driver-vehicle-environment control loop as depicted in Figure 2.2. It combines aspects of the information-processing theory of Wickens, Hollands, Banbury, and Parasuraman (2013) and aspects of regular control theory. The driving task is considered to be a pursuit control (Bubb, 2015a), although it is argued that it is rather a combination of pursuit and compensatory control (Bubb, 2015a). Considering the driving task a compensatory control, the sum of reference and system output in Figure 2.2 would take place not within the information processing, but previous to the perception. The driving task, as described above, represents the reference signal which the driver perceives via his sensory system and processes. Deviations of the system output are assessed and necessary system inputs for reducing this error are derived. The vehicle transforms the driver's input and thus determines the system output. As the driver is part of the closed control loop and continuously contributes to the system output, he is considered to be “in-the-loop”. This manual control was the focus of huge research efforts over the last few decades in order to describe and model the driver and his abilities and behavior.

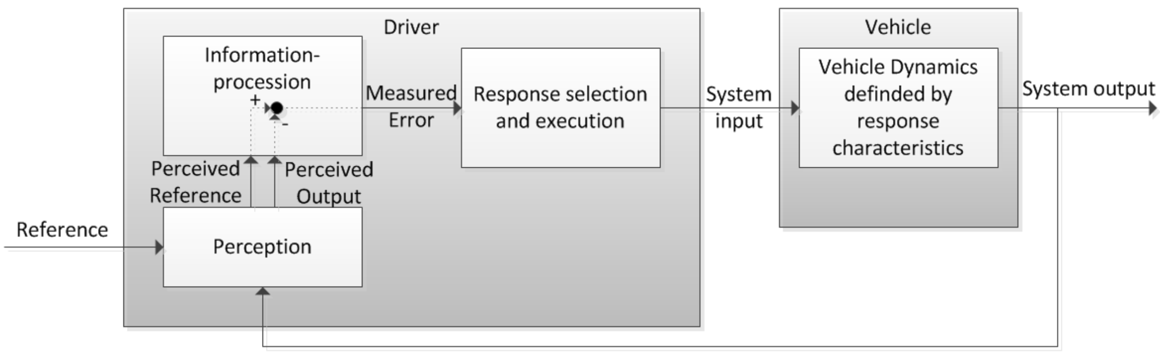



Figure 2.2: Driver-vehicle-environment control loop (based on Wickens et al. (2013) and Bubb (2015a)).

## 2.2 Perception and Cognition

Driving a vehicle is based on different processes of perception and cognition. When driving, a variety of different stimuli are available to the driver. In order to continuously select and execute a response to the control system's output, the driver has to perceive the relevant stimuli such as the environment, the current vehicle state, its parameters, and the reference representing the goal he wants to achieve with the selected response. To derive a basis for decision-making, the perceived stimuli have to be processed and matched with short-term memory and previous experiences. Both the perception and processing of information need attention resources, which are physiologically limited. This process is described by Wickens et al. (2013) and depicted in Figure 2.3. Because of the limitation of attention resources, performing non-driving-related tasks while driving impairs driving performance. Many other effects, for example what is referred to as the "looked-but-failed-to-see" (Herslund & Jørgensen, 2003) effect, can be described using the model of Wickens et al. (2013). As this model can also be applied to effects arising with automated driving, the model is an important basis of considerations within this thesis. The subdivision of information processing into information perception, cognition, decision, and execution is formulated in accordance with other models, e.g. by Schlick, Bruder, and Luczak (2010), or similar to Endsley (1988), although the cognition step is replaced by projection in this case.

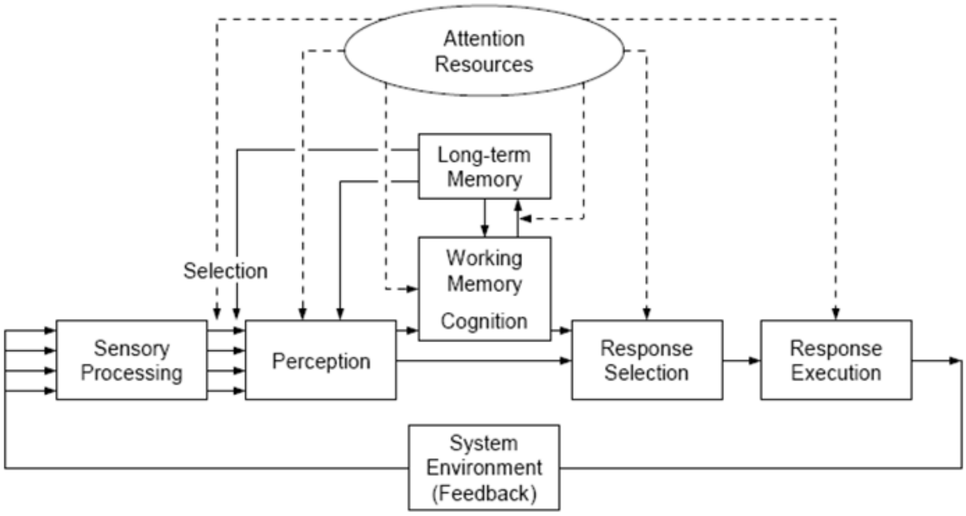



Figure 2.3: Model of human information processing (Wickens et al., 2013).

In experiments with mice, Robert Yerkes and John Dodson (Yerkes & Dodson, 1908) found an effect that was assigned to human performance later on and named Yerkes-Dodson Law (Teigen, 1994) or "Inverted U Function" as shown in Figure 2.4. This principle reveals a correlation between performance and the arousal level, namely "that there is an optimum level or most desirable amount of arousal for any activity" (Basavanna, 2000, p.465), while the level of arousal is being defined as "a general pattern of bodily response in which several psychological systems are activated at the same time including heart rate, sweat gland, activity and EEG" (Basavanna, 2000, p. 25). Low arousal levels (simple, monotonous tasks) as well as very high levels (difficult, complex tasks) lead to reduced performance. As the model of information processing by Wickens et al. addresses impaired performance due to high, but not low arousal, the Yerkes-Dodson Law extends this model moderated by a performance aspect. For the manual control of a road vehicle, this underload arises in very monotonous circumstances such as traffic jams or long night drives, whereas overload occurs predominantly in very demanding situations, for example when experiencing excessive stress while driving. Besides, the Yerkes-Dodson Law also has implications for automated driving, as automation may bidirectionally influence the arousal and therefore impair human performance.

There are many other factors interfering with human performance. The concept of workload plays an important role and is defined "as the mental effort that the human operator devotes to control and / or supervision relative to his capacity to expend mental

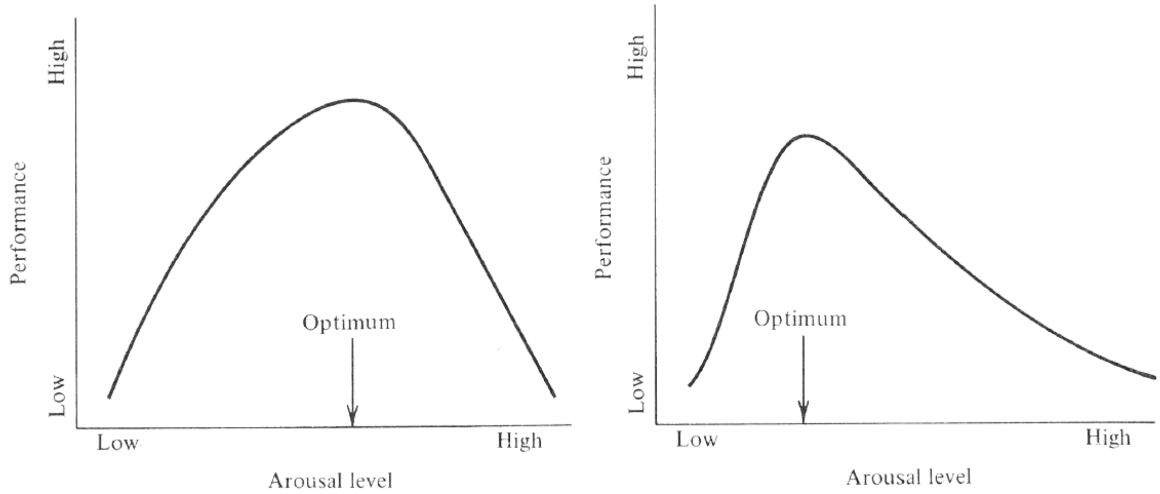



Figure 2.4: Inverted U function for simple (left) and difficult (right) tasks (Klein, 1982).

effort" (Moray, 1979, p. 236), while "capacity of a human operator is the limiting level of performance on any action which is part of a task" (Moray, 1979, 263). Following this definition, Wickens (2008b) states that workload is closely related to the multiple resource theory and therefore affects information processing as depicted in Figure 2.3. High levels of workload claim more attention resources and thus deteriorate a person's ability to perceive and process information.

In the context of automated driving, results show that workload significantly decreases (Winter, Happee, Martens, & Stanton, 2014). This could lead to underload, which is likely to pose a problem (Young & Stanton, 1997) related to the reduced performance due to low arousal levels according to the Yerkes-Dodson Law. This is not exclusively the case, however, as other factors such as aspects of motivation or job satisfaction seem to play a role as well (Moray, 1979).

When looking at human performance, attention is "the focal activity of consciousness leading to heightened awareness of a limited range of stimuli" (Basavanna, 2000, p. 29) and an important construct that was already included in the model of information processing and which is also related to arousal (Kahneman, 1973). As information processing is dependent on attentional resources (Wickens et al., 2013), apparently a lack of attention due to limited resources, for example when performing multiple tasks or when there is a focus of attention on the "wrong" task, deteriorates human performance. The multiple resource theory, derived from the research of different authors (Moray, 1967; Kahneman, 1973; Wickens, 2008b), claims that attention resources can be divided into different segments that differ, for example, with regard to the modalities of perceptional channels. While tasks requiring attention from different segments can be executed simultaneously with only small impairments on performance, tasks requiring attention from the same segment compete for the same attention resources and therefore distinctly deteriorate human performance. When performing non-driving-related tasks such as writing a text message while driving, for example, visual attention resources have to be allocated between the driving task and the text task, so that driving performance is impaired, which is also referred to as **distraction** (Bengler, 2014) and which has a long tradition in human factors research.

In human memory, experiences and previous contacts with a certain task are stored and used for recognizing and solving similar or different / unknown tasks. With increasing experience, the information process is performed faster and fewer attention resources are required. Rasmussen (1983) describes this effect and distinguishes between three general skill levels (cf. Figure 2.5). New tasks are normally handled based on knowledge and under use of problem-solving mechanisms such as the trial-and-error principle. Based on these mechanisms and experiences, humans derive rules for achieving certain goals, while the rules that have proved successful are stored. If the rules can be applied to solve a certain task, the process is referred to as rule-based behavior and belongs to the second skill level. Rule-based behavior is faster than knowledge-based behavior and requires fewer resources. With higher training levels, task handling reaches the faster skill-based level that can be allocated to the psychomotor processes and requires only few resources. Skill-based behavior is developed by excessive training and executed without conscious control. Persons normally cannot report how they derived a decision or executed an action.

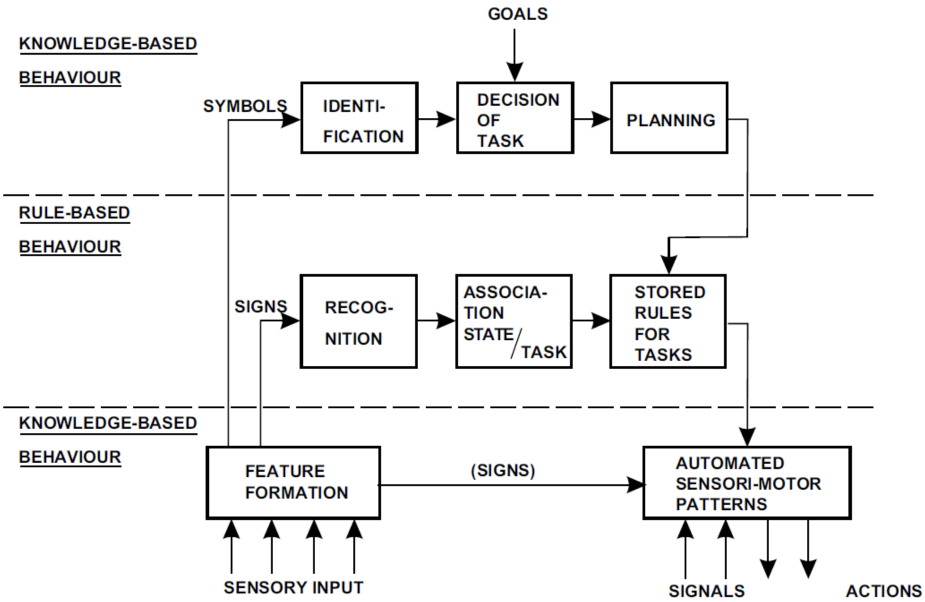



Figure 2.5: Skill levels defined by Rasmussen (1983).

The thesis proceeds on the following summary of above-mentioned models: human information processing and thus task handling increases in speed and performance with experience and training, and information processing is further dependent on the attention resources available, which are affected by arousal, focus of attention and workload.

## 2.3 Automated Driving

Efforts of automating the driving task in the public space must follow the same goals regarding safety as manual driving, described in Section 2.1. When talking about automated driving, the automation of parts of the primary driving tasks is addressed, particularly, but not exclusively, the stabilization and maneuvering of the vehicle.
The idea of automating the driving task was first documented in 1925 in an article in the New York Times (New York Times, 1925). General Motors showed their vision of the future at the 1939 New York World's Fair, which included the development of automated cars until the 1960s (Geddes, 1940). The vision was followed by the *GM Firebird Concept III* featuring "automated steering, which could be adapted to an Auto-Control highway" (Electronic Chauffeurs, 1959, p. 875). Up to 1979, the concepts regarding automated driving had in common that they were dependent on elements in the infrastructure such as inductive guidance, implemented in the road surface (Guang Lu & Tomizuka, 2002).

A rover, introduced by Moravec (1980), was the first approach that was independent from infrastructural preconditions, as it moved and avoided obstacles only based on the view of a camera. In the 1980s, several projects such as the *ALV* (Schefter, 1985), *CMU* (Goto & Stentz, 1987) and the VaMoRs (Dieckmanns, 1989) followed. Further efforts were made entering the 1990s, for example with the projects *PROMETHEUS* (Williams & Preston, 1987), *PATH* (Shladover, 2006), or *NAVLAB* (Thorpe, Herbert, Kanade, & Shafer, 1991). "These projects have significantly advanced research in sensor hardware and software" (Bengler et al., 2014, p. 10) and remarkable results, such as a long-distance drive of 1,750 kilometers with speeds of up to 180 km/h from Germany to Denmark in 1995 and with a share of automated driving of about 95% (Maurer, Behringer, Furst, Thomanek, & Dickmanns, 1996) were achieved.

Based on the progress in automated driving, with the beginning of the century, the Defense Advanced Research Projects Agency (DARPA) announced three Challenges: *Grand Challenge I* in 2004, *Grand Challenge II* in 2005 (Buehler, Iagnemma, & Singh, 2007) and the *Urban Challenge* in 2007 (Buehler, Iagnemma, & Singh, 2009). Several teams from different countries competed in developing automated vehicles and further encouraged automated driving research. Vehicles, in some cases directly resulting from the DARPA challenges, quickly entered public roads for example *Leonie* (Wille, Saust, & Maurer, 2010), *AutoNOMOS* (Rojo, Rojas, & Raul, 2007), or the *Google Car* (Markoff, 2010). At the same time, different research projects were launched, focusing, for example, on urban environments, such as the *CityMobil* project (van Dijke & van Schijndel, 2012), and considering human factors issues in case of system failures or unexpected events (Toffetti et al., 2009).

The efforts in automated driving research were accompanied and empowered by the development of driver assistant systems and ADAS, which enhanced integrated and active safety (Bengler et al., 2014). Starting with systems like the Anti-lock Braking System (ABS) or the Electronic Stability Control (ESC), drivers were assisted in situations of excessive demand arising from the driving task. Longitudinal control was further supported by distance warning systems (Mitsubishi in 1992) and later successively extended by deceleration via throttle (Mitsubishi in 1995) and active braking (Mercedes-Benz in 1999). For lateral vehicle guidance, a similar evolutionary path from lane departure warning systems towards active Lane Keeping Assistant Systems (LKAS) in 2002 is observable (Winner & Hakuli, 2015). Additionally, the first in-vehicle navigation systems were installed in series vehicles in 1989 (Akamatsu, Green, & Bengler, 2013). Different sensors were used for enabling the different system functions of ADAS. The sensors had to be developed to meet the demands of series production regarding cost and reliability, further promoting sensor-related research and technology.

Simultaneously, due to advances in sensor and information technology, automated driving became an increasingly realistic scenario for series vehicles in the near future. The idea of implementing automated functions in regular vehicles quickly evolved during the last few years, leading to further intensified research and several press releases of different Original Equipment Manufacturers (OEM) and tier-one suppliers, announcing that hands-free driving would b achieved between 2020 (Preisinger, 2013; *Continental Strategy Focuses on Automated Driving*, 2012) and 2025 (Bereszewski, 2013). In this context, numrous joint research projects have recently been launched, for example on a European level with the AdaptIVe (Langenberg, Bartels, & Etemad, 2014), HAVEit (Hoeger et al., 2008) or D3CoS (Zimmermann & Bengler, 2013) projects, or on a national level, for example with the KoHAF (ZENTEC GmbH, 2015) project. This exemplary selection of projects emphasizes the huge effort that is being made in order to enable automated vehicle functions in general and HAD in particular.

## 2.4 Levels of Vehicle Automation

The various activities in the field of automated driving research and the emerging of automated functions for vehicle guidance have led to a need for definitions and classifications, to support a common understanding across domains and to facilitate the exchange of knowledge. Based on results of a body of experts, Gasser (2012) from the public German road agency Bundesanstalt für Straßenwesen (BASt) has published a definition of different vehicle automation levels (Gasser & Westhoff, 2012) (cf. Figure 2.6), subdividing vehicle automation into five stages.
The level Driver Only corresponds to manual driving, possibly under the presence of lower levels of driver assistance. ADAS executing either longitudinal or lateral guidance are considered to belong to the Driver Assistance level. Examples are the Adaptive Cruise Control (ACC) or Active Lane Assist. In Partial Automation, both longitudinal and lateral guidance are conducted by an automated system, but the driver "shall permanently monitor the system" (Gasser & Westhoff, 2012, p. 3). As Gasser does not further define the term "monitor", the Traffic Jam Assist (TJA) or systems like the *DISTRONIC PLUS with Steering Assist* introduced by Mercedes Benz in 2014 can be considered partial automation, although drivers have to keep their hands on the steering wheel (Mercedes-Benz, 2015) as a part of the monitoring task. High Automation, or HAD, is defined similarly as Partial Automation, but the driver is "no longer required to permanently monitor the system" (Gasser & Westhoff, 2012, p. 3). Instead, the driver is allowed to deal with other tasks than driving, but must take over "control with a certain time buffer"

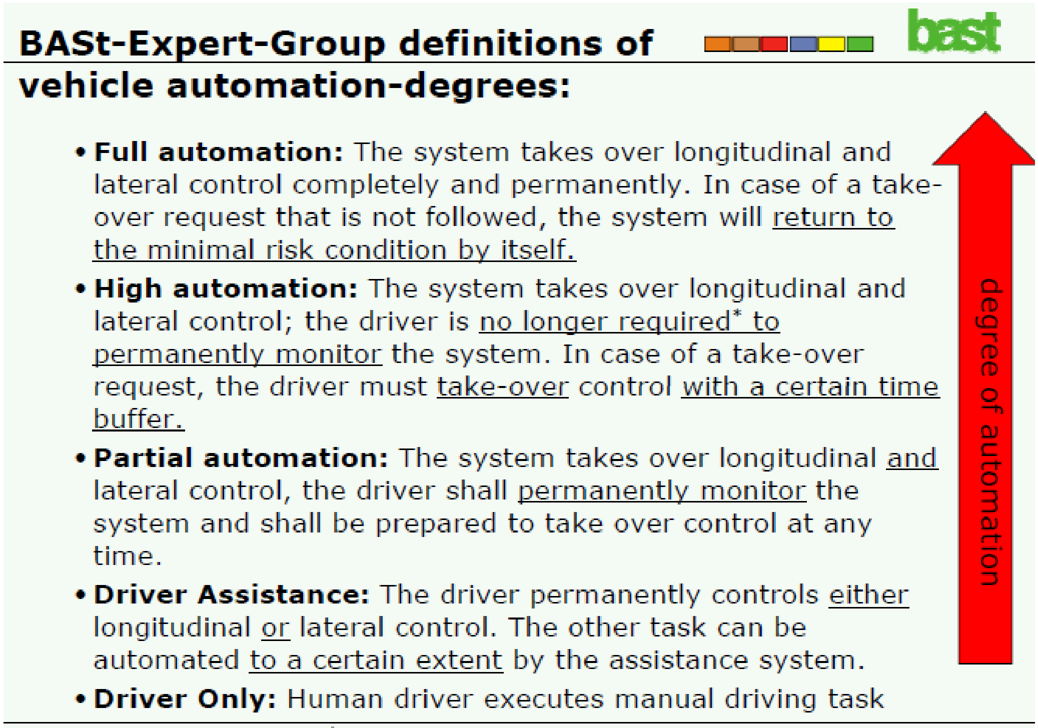



Figure 2.6: Automation levels, defined by the BASt.

(Gasser & Westhoff, 2012, p. 3). This implies that the driver is still needed as a fallback level of the automation. The highest automation level in the taxonomy of the BASt is Full Automation. Here, the automated system is able to “return to the minimal risk condition by itself” (Gasser & Westhoff, 2012, p. 3), meaning that if the driver fails as fallback level, the system initializes a maneuver that reduces the risk of someone getting harmed.

In 2013, the American National Highway Traffic Safety Administration (NHTSA) defined automation levels (NHTSA, 2013) similar to the ones of the BASt. The five levels are named ascendingly from “Level 0 - No Automation” (BASt: Driver Only) up to “Level 4 - Full Self-Driving Automation” (BASt: Full Automation). Just as with the High Automation level in the BASt-taxonomy, the NHTSA defined its “Level 3 - Limited Self-Driving Automation” as a system where the driver does not have to permanently monitor the system, but “is expected to be available for occasional control, but with sufficiently comfortable transition time” (NHTSA, 2013, p. 5) (see full definition on page 11).

> ***Level 3 - Limited Self-Driving Automation:*** *Vehicles at this level of automation enable the driver to cede full control of all safety-critical functions under certain traffic or environmental conditions and in those conditions to rely heavily on the vehicle to monitor for changes in those conditions requiring transition back to driver control. The driver is expected to be available for occasional control, but with sufficiently comfortable transition time. The vehicle is designed to ensure safe operation during the automated driving mode. An example would be an automated or self-driving car that can determine when the system is no longer able to support automation, such as from an oncoming construction area, and then signals to the driver to reengage in the driving task, providing the driver with an appropriate amount of transition time to safely regain manual control. The major distinction between level 2 and level 3 is that at level 3, the vehicle is designed so that the driver is not expected to constantly monitor the roadway while driving.(NHTSA, 2013)*

The Society of Automotive Engineers (SAE) also defined vehicle automation levels (SAE International, 2014). It distinguishes between six levels, one more level than BASt and NHTSA. Figure 2.7 provides an overview of the three definitions. The SAE levels 0, 1 and 2 correspond to the definitions of first levels defined by BASt and NHTSA, whereas higher levels show deviations. BASt Highly Automated and NHTSA level 3 are further subdivided into two levels in the SAE definition. SAE level 3, which is also referred to as Conditional Automation cannot deal with a failure of the driver to respond to a request to intervene, while a SAE level 4 High Automation system is capable of dealing with a driver who does not "respond appropriately" (SAE International, 2014, p. 2). It is questionable if this distinction is necessary, as there might not be a realistic use case for a SAE level 3 system, "since the automation system should continue to control the vehicle in case that the driver cannot take over the driving task" (Amditis et al., 2013, p. 160). It further has to be mentioned that this distinction leads to inconsistencies between the definitions, as SAE High Automation refers to another level than the BASt High Automation (Conditional Automation in SAE). Regarding SAE level 5 - "Full Automation" definitions are similar just like at lower levels of automation. All three definitions of Full Automation guarantee the security of the system in all situations, without the need for any contribution of the driver.

This thesis examines the take-over of the driving task in NHTSA level 3, SAE Conditional Automation, and BASt Highly Automated driving (HAD). Whenever the expressions "highly automated", "high automation", Highly Automated Vehicle (HAV), or HAD are used, they refer to those definitions and differ explicitly from the SAE definition of high automation (Level 4).

> ***Take-Over.***
> Transition from higher levels of automated vehicle guidance to manual or assisted driving by reallocating control of the driving task back to the driver.

| SAE level | SAE name | SAE narrative definition | Execution of steering and acceleration/ deceleration | Monitoring of driving environment | Fallback performance of *dynamic driving task* | System capability (*driving modes*) | BASt level | NHTSA level |
|---|---|---|---|---|---|---|---|---|
| ***Human driver*** **monitors the driving environment** | | | | | | | | |
| **0** | **No Automation** | the full-time performance by the *human driver* of all aspects of the *dynamic driving task*, even when enhanced by warning or intervention systems | Human driver | Human driver | Human driver | n/a | Driver only | 0 |
| **1** | **Driver Assistance** | the *driving mode*-specific execution by a driver assistance system of either steering or acceleration/deceleration using information about the driving environment and with the expectation that the *human driver* perform all remaining aspects of the *dynamic driving task* | Human driver and system | Human driver | Human driver | Some driving modes | Assisted | 1 |
| **2** | **Partial Automation** | the *driving mode*-specific execution by one or more driver assistance systems of both steering and acceleration/deceleration using information about the driving environment and with the expectation that the *human driver* perform all remaining aspects of the *dynamic driving task* | **System** | Human driver | Human driver | Some driving modes | Partially automated | 2 |
| ***Automated driving system*** **("system") monitors the driving environment** | | | | | | | | |
| **3** | **Conditional Automation** | the *driving mode*-specific performance by an *automated driving system* of all aspects of the *dynamic driving task* with the expectation that the *human driver* will respond appropriately to a *request to intervene* | System | **System** | Human driver | Some driving modes | Highly automated | 3 |
| **4** | **High Automation** | the *driving mode*-specific performance by an *automated driving system* of all aspects of the *dynamic driving task*, even if a *human driver* does not respond appropriately to a *request to intervene* | System | System | **System** | Some driving modes | Fully automated | 3/4 |
| **5** | **Full Automation** | the full-time performance by an *automated driving system* of all aspects of the *dynamic driving task* under all roadway and environmental conditions that can be managed by a *human driver* | System | System | System | **All driving modes** | | |

Figure 2.7: Automation levels, defined by the SAE (SAE International, 2014).

## 2.5 Change of Paradigms

Automating the driving task seems to be the next consecutive step in a world of increasing driver assistance. In fact, automated systems are based on ADAS, concerning sensor technology as well as implemented functions and the integration into the Human Machine Interface (HMI). The appearance of systems like the TJA does not obviously differ from what drivers are used to from ADAS. Furthermore, automated systems can partly be implemented by merely joining functions of already existing ADAS. Nevertheless, concerning the interaction principles between driver and vehicles, introducing partially and highly automated systems in road transportation will lead to a change of paradigms just like the introduction of the automobile in a world moved by horses and coaches.

An incremental approach may not be sufficient to address the urgent topics accompanying the development of automated vehicle guidance. Removing the driver from control adds new questions of concern to human factors researchers (Akamatsu et al., 2013) and to other domains that distinctly differ from questions that emerged with ADAS as depicted below.

- **Mobility.** As driving automated vehicles is assumed to reduce workload and increase comfort, mobility behavior is likely to change. Even if the possibility of an extended group of possible drivers / passengers is not considered, automated driving may lead to more and longer drives. The time spent in the vehicle could be used for office-related tasks, or for any kind of entertainment, so that longer drives become more likely. This challenges the prospect of reducing fuel consumption and congestion, as traffic volume may increase disproportionately to a possible gain in efficiency due to a smoother traffic flow.

- **Safety.** Increasing traffic safety and reducing fatalities is one of the most frequently mentioned motivators for automated driving. This relation seems obvious, as humans are regarded as the major cause of accidents (cf. Treat et al., 1979; National Highway Traffic Safety Administration, 2008). Nevertheless, there is a number of very successful and effective control actions by the driver which are not to be underestimated. Drivers perform very well and do have a good reliability, proved by a significantly low number of accidents per mile driven. Drivers are able to manage new and very complex situations and have good anticipation abilities. Especially the latter is complicated to implement into automated systems, as “most of the environmental states are not directly observable” (Gindele, Brechtel, & Dillmann, 2010, p. 1625). Before a safety gain due to an automated system could take effect, those systems would have to be able to perform at least at an equivalent level to a driver in all the situations currently not leading to accidents because of a successful driver input and communication. Furthermore, even if the crash probability per mile driven decreases, the above-mentioned possible increase in traffic volume may lead to a higher absolute number of crashes within the transport system.

- **Law and Ethics.** In manual driving as well as in partially automated systems, the driver is responsible for his vehicle and has to intervene if the system fails. As soon as the driver is removed from this closed loop and allowed to deal with tasks other than driving, he cannot be held responsible for the actions the automation conducts. It still is questionable who or which organization will be liable for automation-induced accidents or failures. Besides, there are a lot of different ethical questions arising that have to be discussed and solved. Drivers cannot be blamed for wrong decisions they probably made intuitively within fractions of seconds in emergency situations. An automated system can consider numerous different solutions in a split second, including those that reduce the risk for other road users but simultaneously increase the risk for the driver.

- **The Driver.** Figure 2.8 depicts the enhancement of the driver-vehicle-control loop (Section 2.1) by introducing vehicle automation. The driver neither continuously contributes to the system output nor, in dependence of his current attention focus, does he perceive the system output, indicated by the dashed lines. Therefore, the driver is considered to be out-of-the-loop. Taking the driver out of the loop leads to performance problems, known from other domains such as aviation (Endsley & Kiris, 1995). Several researchers assume that similar effects will arise by automating the driving task (Stanton & Marsden, 1996; Young & Stanton, 1997). Humans are not made to sit and stare (Reason, 1990) and performance decreases after a maximum of 15 minutes (Othersen, Petermann-Stock, & Vollrath, 2014). As soon as the driver is released from the monitoring task by introducing HAD, the workload decreases (Young & Stanton, 2007b), which could lead to underload (Young & Stanton, 1997) and thus reduced performance (Yerkes & Dodson, 1908). Participants are therefore more likely to engage in non-driving-related tasks (Carsten, Lai, Barnard, Jamson, & Merat, 2012) and they were measured to be less likely to intervene in critical situations (Stanton, Young, Walker, Turner, & Randle, 2001; Waard, Hulst, Hoedemaeker, & Brookhuis, 1999).
  This correlates with possible problems due to mode awareness (Sarter & Woods, 1995), an uncertainty of the current allocation of responsibilities regarding the driving task. Several other automation effects are also likely to emerge (Parasuraman & Riley, 1997), among them skill degradation (Stanton, Young, & McCaulder, 1997), possibly leading to accidents in situations where automation would not be considered to be an issue. The misuse and abuse (Parasuraman & Riley, 1997) of automated systems correlate with effects such as complacency (Parasuraman & Manzey, 2010; Reichenbach, Onnasch, & Manzey, 2010; Körber & Bengler, 2014) and could further affect traffic safety. Results indicate that in higher automation levels, drivers increasingly fail to detect and handle system failures (Shen & Neyens, 2014; Strand, Nilsson, Karlsson, & Nilsson, 2014). Hence, take-over situations in HAV become very challenging for the driver. They will probably occur in complex scenarios, as those are most likely to overexert the automation. Additionally, they are possibly time-critical and occur out of a rather undefined driver state. It must be ensured that the driver is able to perceive the relevant information, develop a strategy for solving the take-over and execute an appropriate maneuver. For this reason, several design considerations apply (Beukel & Voort, 2014a) in order to ensure safety of the driver-vehicle-automation system (Gold, Körber, Lechner, & Bengler, 2016).

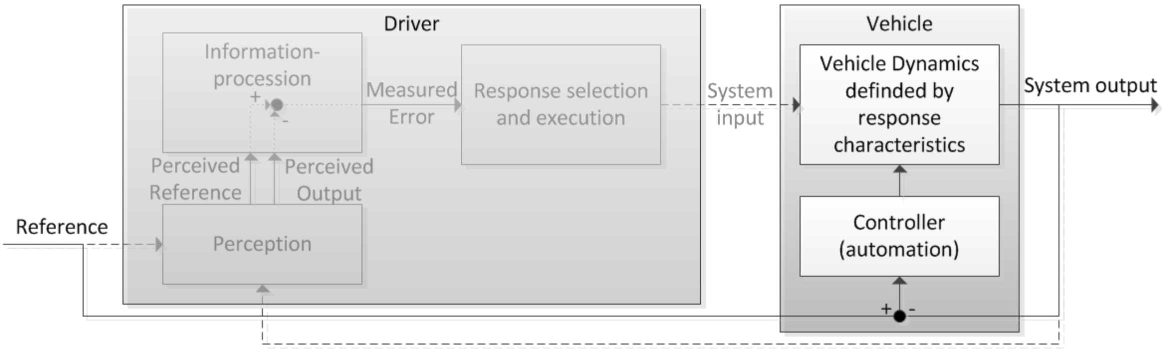



Figure 2.8: Automation-vehicle-environment control loop (based on Wickens et al. (2013) and Bubb (2015a)).

## 2.6 The Take-Over in Highly Automated Vehicles

### 2.6.1 Technical Realization of Automated Driving

As illustrated in Section 2.3, partially automated systems are already entering the market and highly automated driving is likely to enter series production within the next decade. While level 2 systems do differ from level 3 concerning driver demand, driver interface as well as ethical and legal requirements, the functional realization of automated vehicle guidance in those systems is rather similar. In order to gather information on the driving environment, a set of different sensors is employed to generate a 360-degree image of a vehicle's surroundings (Figure 2.9). The sensors used are briefly described in the following, as an understanding of the technical background is beneficial for assessing controllability of HAVs. Detailed knowledge is provided for instance by Winner and Hakuli (2015).

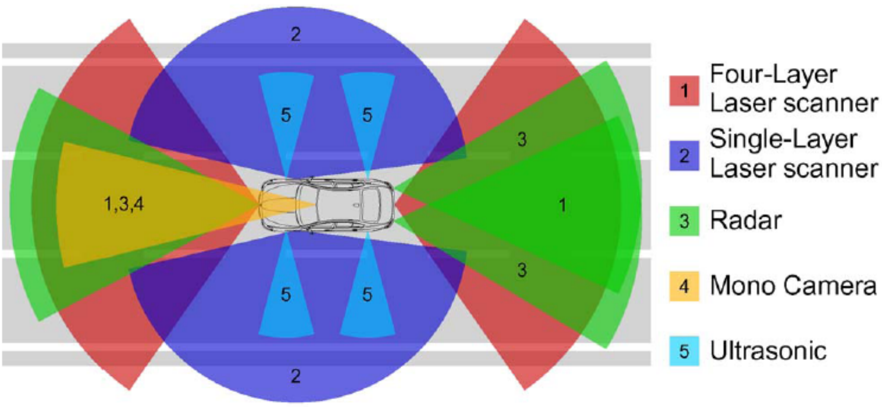



Figure 2.9: Sensor configuration for highly automated vehicles (Aeberhard et al., 2012).

- **Mono Camera.** Monocular camera systems are widely used in the road vehicle domain, for example for ego-motion estimation (Yamaguchi, Kato, & Ninomiya, 2006) or pre-crash detection of objects (Zehang, Miller, Bebis, & DiMeo, 2002).

Driving-relevant attributes can be extracted by image processing and supplied for higher evaluation processes (Winner & Hakuli, 2015). The economical sensors are the basis for many Advanced Emergency Braking Systems (AEB) and are also used for lane detection (Felisa & Zani, 2010), which is required in current steering support systems.

- **Stereo Camera.** Similar to systems in the early 1990s, images retrieved from a stereoscopic camera are an important data source for environmental perception. By recording images from different angles, stereo cameras allow depth detection and therefore the orientation in three-dimensional space. They are used for object detection (Baig, Aycard, Vu, & Fraichard, 2011), detection of patterns such as lane markings (Bertozzi & Broggi, 1998), and for recording accurate maps (Broggi, Buzzoni, Felisa, & Zani, 2011), wich is important for automated vehicle guidance. As extracting useful information from relatively large amounts of video data is difficult (Broggi et al., 2011), different algorithms are currently being developed (e.g. Dai Bin, Liu Xin, & Wu Tao, 2005; Ranft & Strauß, 2014), enabling real-time processing of high-resolution video images (Mark, van der W. & Gavrila, 2006). With 40 to 100 meters, the range of stereoscopic cameras is rather limited (Bajracharya, Moghaddam, Howard, Brennan, & Matthies, 2009; Dickmann, Appenrodt, & Brenk, 2014; Hadsell et al., 2009).
- **LIDAR.** Laser Illuminated Detection And Ranging (LIDAR) sensors are optical sensors which scan the environment by emitting (pulsed) laser light and analyze intensity (reflectivity) and phase shift of the reflections (distance). Depending on the sensor's design, one (Lu & Tomizuka, 2006) or multiple layers (Moras, Cherfaoui, & Bonnifait, 2010) are recorded. In common LIDAR sensors that are used for research purposes or in the DARPA challenges, up to 64 lasers work in parallel (Velodyne Scoustics Inc., 2014). The range of LIDAR sensors differs between the systems and depends on the reflectivity of the surface. Declarations differ between 50 meters for pavements (Velodyne Scoustics Inc., 2014), 100 meters (Lindner & Wanielik, 2009), 150 meters for objects with good reflectivity (Velodyne Scoustics Inc., 2014; Lu & Tomizuka, 2006), and reach up to 200 meters (Moras et al., 2010). In HAD they are used for detecting the road and road-edge (W. Zhang, 2010), vehicles (Guang Lu & Tomizuka, 2002), and other moving objects (Baig et al., 2011) as well as lane markings (Kammel & Pitzer, 2008; X. Chen et al., 2009).
- **Radar.** Radar technology entered the conventional vehicle domain with the *Distronic*, an ACC-system of Mercedes Benz (Marsden, McDonald, & Brackstone, 2001). The sensor emits pulsed electromagnetic waves and detects the reflections of objects and terrain. There are Short Range Radar (SRR) systems (24 GHz) with a range of about 30 meters and Long Range Radar (LRR) (77 GHz) with a range of about 150 meters (Wenger, 2005). Requirements for the sensor-range of future LRR in HAVs are in the region of 200 meters (Dickmann, Appenrodt, Bloecher, et al., 2014; Wenger, 2005). In automated vehicles, radar is also used for the purpose of map building (Kimoto & Thorpe, 1998).
- **GPS.** Global Positioning System (GPS) tracks vehicles position by comparing time stamps, received from geostationary satellites. Although the accuracy of GPS lies

within a range of approximately 3 meters (Bajaj, Ranaweera, & Agrawal, 2002), the position can be estimated more accurately in combination with other sensors. The more elaborate and costly Differential Global Positioning System (DGPS) uses ground-based reference stations to enhance accuracy up to a few centimeters, allowing accurate positioning of the vehicle within a single lane (e.g. Moon, Kim, & Lee, 2012).

- **Accelerometer.** Accelerometers are commonly used sensors for assessing accelerations and spatial position of the vehicle. They are widely used for ADAS such as the Electronic Stability Program (ESP). In the field of vehicle automation, acceleration data is used for several purposes, including a plausibility check of other sensor data as well as data fusion.
- **Ultrasonic Sensors.** In addition, ultrasonic sensors, known from parking assistant systems, are used for detecting nearby objects, such as vehicles in the neighboring lanes (Aeberhard et al., 2012).

Future HAVs will further profit by vehicle-to-vehicle, vehicle-to-infrastructure or other communications (Vehicle-to-X communication (V2X)) (Bengler et al., 2014; Günthner, Schmid, Stählin, & Jürgens, 2014). Several projects have already shown the successful application of V2X systems in the field of automated driving (e.g. Geiger et al., 2012; Fuchs, Hofmann, Löhr, & Schaaf, 2015). Furthermore, in order to enable HAD, accurate maps including landmarks and continuous updates are necessary. The data of the sensors listed are fused within the automation software on different levels (Amditis et al., 2013; Becker, 2000), objects are classified (Niknejad, Takahashi, Mita, & McAllester, 2011; Baig et al., 2011), and safe paths calculated, which referred to as trajectory planning (S. Zhang, Deng, Zhao, Sun, & Litkouhi, 2013; Glaser, Vanholme, Mammar, Gruyer, & Nouveliere, 2010). Redundancies are crucial here in order to guarantee validity of data, accuracy of trajectory planning and reliability (Aeberhard et al., 2012). It is ensured that every object is captured by at least two independent sensor systems, for instance radar and LIDAR. Thus, object recognition is still feasible in the case of single sensor failures. Otherwise it would hardly be possible to prove the controllability of the system. There are ways of detecting these sensor failures (Bouibed, Aitouche, & Bayart, 2010), although the effort of failure recognition is very high, especially in safety-critical systems (Dziubek, Winner, Becker, & Leinen, 2012). There are various types of possible sensor failures such as glare by sunlight or headlights of other vehicles, dirt on the sensors, destruction (e.g. by stone chip), or software shortcomings.

### 2.6.2 Causes for a Take-Over

The above-noted effort will likely enable automated driving, initially on highways. Nevertheless, there will still be scenarios where the driver is needed as a fallback level and has to take over vehicle control again. From the current point of view, the exact circumstances of take-over scenarios cannot be predicted, as further information of the capabilities of HAVs is vague. There are, however, different types of reasons for a machine-initiated take-over of the driving task (cf. Table 2.1).

According to Geyer et al. (2014), there is a differentiation between situations and scenarios. Adopted for the take-over, take-over situations are represented by a localized and specific set of criteria and their current state, whereas take-over scenarios include the set within which a take-over may occur and include at least one take-over situation. A stranded vehicle blocking the current ego-vehicle's lane on a three-lane highway would be considered a take-over scenario. The driver-vehicle system responding to the Take-Over Request (TOR) in this scenario and evading to the left lane would be a take-over situation.

> ***Automation Scenario.*** Environmental conditions that allow the usage of the automated system.

> ***Take-Over Scenario.*** Environmental conditions among which a take-over is conducted.

> ***Take-Over Situation.*** Temporary and localized conditions among which a take-over is conducted.

- **End of automation scenario.** It is assumed that HAD will initially be available on highways and probably only on certain routes. Thus, the automation scenario is limited and a take-over will be necessary when approaching the end of an automation scenario, for example when exiting the highway. As such boundaries are map-based and stationary, the driver can be informed and retrieved in a timely way. The automation scenario will also be dependent on driving conditions such as daylight, fog, snow, ice, rain, or others. If conditions change to improper states, the driver is required to regain control.
- **Failure of sensors.** As HAD is enabled by a large set of sensors, the availability of HAD strongly depends on the accuracy and availability of sensor data. Sensors are redundant and a failure of single sensors does not necessarily imply a sudden break down of automated vehicle guidance. Nevertheless, the range of object detection could be reduced and the lack of sensor redundancy impairs safety (degradation of the automated system). The driver will have to re-engage by monitoring the system or taking over vehicle control completely. If several sensors fail simultaneously, the vehicle may be guided based on the last available image of the environment for a few seconds, without the ability to recognize further changes in the environment. The time budget for taking over control would be very limited, in accordance with the above mentioned sensor ranges.
- **Situation-related take-over.** Apart from the end of the automation scenario described above, situation-related aspects within the automation scenario could cause a TOR. Although HAVs will be able to deal with most of the situations occurring on public roads, there will still be situational conditions the automation is not capable of dealing with. This could either be the detection of objects the system is not able to classify, inconsistencies that occur while fusing sensor data, a failed classification of scenarios, or scenarios that require a higher level of anticipation or communication (e.g. persons in/next to the road). Those scenarios are likely to be detected based

on on-board sensor data and therefore within the range of the sensors. Depending on the vehicle's speed, the time budget for regaining control is limited to a few seconds, also depending on the listed sensor ranges.

Table 2.1: Examples of take-over scenarios

| Scenario | Temporal criticality | Implication |
|---|---|---|
| End of automation scenario: | | |
| Exiting highway | Low | take-over |
| Construction zone (map based) | Low | take-over |
| End of automation scenario (conditions) | Medium | take-over/monitor |
| Failure of sensors: | | |
| Temporary loss of single sensor | Medium | monitor/non |
| Failure of single sensors | Medium | take-over/monitor |
| Failure of multiple sensors | High | take-over |
| Situation-related take-over: | | |
| Map or V2X-based detection of limit | Low | take-over/monitor |
| On-board detection of system limit | High | take-over |
| Situation classified as too complex | High | take-over/monitor |
| Situation/object cannot be classified | High | take-over/monitor |

### 2.6.3 Take-Over Scenarios

As shown in Table 2.1, there are scenarios where monitoring the automation might be sufficient. Although the request for monitoring the HAV brings along some interesting research questions and is part of current research (Gold, Lorenz, Damböck, & Bengler, 2013), this thesis focuses on scenarios requiring a take-over, as the automation is not able to solve a scenario without the driver's intervention. Moreover, time-critical take-over scenarios with a limited time budget are of special interest (Gasser, 2013), as they can be very demanding for the driver and represent the most critical transitions within HAD. They are therefore a valuable tool to assess driver's performance, relevant for controllability aspects of HAVs.

Although there are transitions to manual control triggered by the driver, which may also imply safety-relevant aspects, these are not considered further in this thesis. As the driver causes these take-over situations, he is likely to be prepared to take over control and in a state that allows successful continuation of the driving task. Nevertheless, it should be ensured that automation effects such as skill degradation or the process of task switching do not impair driving performance when drivers initiate a take-over.

In time-critical take-over scenarios caused by a system limit, the demand on the driver is much higher. Because the automation is no longer able to perform the driving task, failure to take over the vehicle's control will necessarily lead to critical situations with a possibly severe outcome. It is therefore of great interest how the driver, who is pressed for time who comes from a state of being a passenger in an automated vehicle, handles such situations.

> ***System Limit.*** Summary of situational conditions that cause the necessity of a take-over or triggers a minimal risk maneuver.

In HAD, all system limits are detected by the system (Gasser, 2012), and the system informs the driver that a limit is approached by emitting a Take-Over Request (TOR). The TOR can be of different types, although several design rules apply. As the driver is allowed to engage in non-driving-related tasks, his eyes are probably off the road and information displays are not in the driver's current field of view. Visual displays for the TOR have to be designed in a way which ensures that his attention is attracted, without depending on the driver's current focus of attention. In the same manner, haptic feedback must be presented in places that are guaranteed to be in contact with the driver. This is why the steering wheel and pedalry are less suitable. Another common modality of presenting warnings is the auditory channel, as it is independent from the direction of drivers' visual attention and physical position. Acoustic warnings seem to represent an advisable way for issuing a TOR. It stands to reason that such TORs should be designed according to existing standards for warnings in the vehicle domain as described, for example, by NHTSA (Campbell, Richard, Brown, & McCallum, 2007).

The perceptual process of the TOR stimulus conforms to common models of human perception as found in Wickens et al. (2013). Due to the occupation with a non-driving-related task, attention resources for perceiving the TOR may be limited, so the stimulus intensity should be large enough to ensure successful perception. The occupancy of cognitive resources could further lead to buffering of the stimulus in the working memory and to delayed processing. This relates to the issue of task switching and the resulting alternation costs. It includes an increase of error probability and delayed reactions in the range of several hundred milliseconds (Nieuwenhuis & Monsell, 2002) when switching from one task (non-driving-related task) to another (driving). In many tasks switching situations, these costs can be reduced by switching tasks in advance, which reduces or eliminates alternation costs (Pashler, 2000; Nieuwenhuis & Monsell, 2002). This strategy fails when taking over vehicle control from HAVs, as the TOR is triggered by the automation. Assuming that there is a limited time budget, such automation-induced delays in perception and processing could extend the take-over in a safety-relevant magnitude. Not least because of these automation effects, the timing and the appropriate design parameters of the TOR will be one of the major research questions in the years ahead.

> ***Take-Over Request.*** Information of stimulative nature, emitted by the automated vehicle with the purpose of initiating a take-over.

Taking over the control from a HAV includes and requires several steps which form the take-over procedure. Perception, processing and initiating a response to the TOR takes fractions of a second, which is considered the reaction time. Subsequently, the driver starts (at best) immediately allocating his attention back to the driving task, most likely by a gaze to the scenery. In dependence of the driver's comprehension of the necessity of

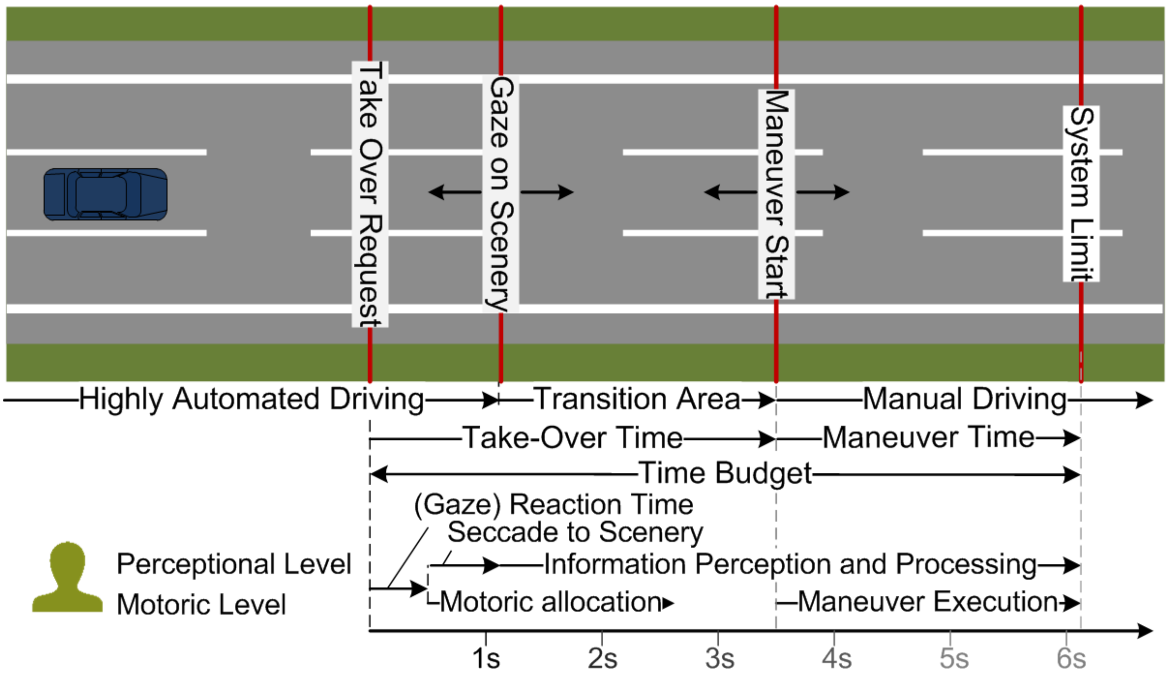



Figure 2.10: Take-over procedure, adopted from Gold and Bengler (2014). Times for reaction, gaze reaction and motoric allocation approximated from Damböck (2013).

taking over vehicle guidance, he will get back in driving position by repositioning his hands on the steering wheel and his feet on the pedalry. The time for this glance and these motion processes can be estimated by looking at motion times, as done by Damböck (2013). Figure 2.10 shows an exemplary take-over procedure. Times for processes on the motoric and perceptional level that are indicated at the bottom are obtained from Damböck (2013). They were measured in a driving simulator experiment, involving an engagement in a non-driving-related task in the center console. Focusing on the scenery again took approximately 1.1 seconds, and repositioning the hands on the steering wheel more than two seconds. The reallocation is followed by processes of information perception and regaining an understanding of the current situation, in dependence of the scenario's complexity. Subsequently or simultaneously, the driver selects and executes a response / maneuver, which requires additional time in dependence on the selected maneuver. The take-over time is the span between the TOR and the start of a maneuver as a reaction to the system limit and must not be confused with the Time Budget (TB). While the Time Budget (TB) represents the time available for the take-over, the take-over time marks the point in time when the transition of the driving task from the automation to the driver can be considered to be complete. This does not imply the time needed for the maneuvering, which can be further impaired by automation effects.

> ***Time Budget.*** Time provided for the take-over and the execution of a maneuver, as an adequate response to the system limit.

Damböck (2013) reasonably constitutes the take-over process as a primarily sequential sequence of actions. This differentiated approach is a promising way of operationalizing the take-over process and assessing the main aspects of a driver's behavior in a HAV. Nevertheless, some steps are considered to be rather parallel, as already indicated in Figure 2.10. A gaze reaction may be performed in parallel to a motoric allocation, and the maneuver execution may be started in parallel to current information perception and processing. Additionally, the description should further be complemented by driver performance aspects, which are required to evaluate the controllability of the take-over in HAVs.

### 2.6.4 Evaluation of Take-Over Situations

The success of the take-over and the quality of the subsequent manual driving can be assessed by timing aspects of the take-over, such as reaction times or the time it takes the driver to take over vehicle control, and by the quality of driver's input, for example by evaluating accelerations. Both timing and quality aspects have to be considered in order to evaluate the take-over performance and to receive a holistic picture (Gold & Bengler, 2014; Lorenz, Hergeth, Kerschbaum, Gold, & Radlmayr, 2015). There is a wide range of driving parameters and other measures that could be considered for assessing the take-over performance. In the following, some assorted and promising parameters are discussed and used in the studies subsequently presented and in the modeling process.

> ***Take-Over Performance.*** Combination of timing and quality aspects of driver's input within a take-over scenario.

#### 2.6.4.1 Timing Metrics of the Take-Over

The take-over is characterized by a temporal sequence of actions. In the case of a system-initiated take-over, it is reasonable to measure times in reference to the moment of the TOR, so that all reported times are time intervals starting with the TOR.

- **GazeReactionTime.** The *GazeReactionTime* $\mathbf{t_{GR}}$ is the first measurable response of the driver and is measured based on the first gaze reaction after the TOR (Damböck, 2013). This measure represents the driver's reaction time, but is further referred to as *GazeReactionTime* to clarify the measures' origin and prevent confusion with other timing measures. It indicates the driver's processing speed and whether the message which the TOR delivers is perceived as urgent, for example due to a high amplitude (Keuss, 1972; Schmidtke, 1961). It is assumed that results from simple reaction time research can be assigned to *GazeReactionTime*. Hence, the modality with which the TOR is presented can have an effect on the *GazeReactionTime* (Green & Gierke, 1984), just like the driver's workload (Makishita & Matsunaga, 2008) due to non-driving-related tasks as also illustrated in Subsection 2.6.3. It can also be assumed that experience with previous take-over situations (Krinchik, 1969) and the trust in automation and thus the expectation regarding the automated function could influence this measure. Additionally, *GazeReactionTime* may depend on many other factors (Welford, Brebner, & Kirby, 1980) such as driver's age (Kováč, 1969), time of day (Höhne, 1974), duration (Schmidtke & Micko, 1964), or arousal (Welford et al., 1980). Moreover, cross-correlations between these factors, for example between driver's age and workload may exist (Cantin, Lavallière, Simoneau, & Teasdale, 2009).

- **EyesOnRoadTime.** After leaving the non-driving-related task, the driver's gaze switches directly to the scenery or passes a visual display first. The following *EyesOnRoadTime* $\mathbf{t_{EOnR}}$ is measured from the TOR until the moment when the driver's gaze has reached the scenery. At this point in time, drivers can start to gather information about the situation and relevant objects to enable the selection of an adequate response. Just like the *GazeReactionTime*, the *EyesOnRoadTime* is dependent on different individual factors, experience and the perceived urgency of the TOR.
- **HandsOnTime.** In order to execute the driving task, at least one hand has to grasp the steering wheel, when considering a conventional vehicle interface, which are brought up for discussion as HAVs may lead to new approaches, for example, transforming steering wheels (cf. Kerschbaum, Lorenz, & Bengler, 2015). The time drivers need to reposition their hands on the steering wheel is referred to as *HandsOnTime* $\mathbf{t_H}$. It is defined as the time between the TOR and the moment when at least one hand touches the steering wheel. Although it indicates the speed for returning to a driving position, it does not necessarily imply complete physical readiness to continue with all aspects of the driving task. For this reason, readiness to brake or execute a steering maneuver cannot be derived from this measure. The measure is dependent on the driver's position previous to the TOR and on motion times. Just like with the *GazeReactionTime*, correlations with urgency of the take-over, individual predispositions and with previous experiences are likely to exist.
- **Take-OverTime.** The *Take-OverTime* $\mathbf{t_T}$ is defined as the time from the TOR until the driver takes over the primary driving task. Defining this point in time is not trivial, as a successful execution of the driving task should imply a cognitive understanding of the situation. If the take-over scenario only requires lateral stabilization of the vehicle, the transition is rather fluent and the moment of active driver input hard to define, as seen in a study by Merat, Jamson, Lai, Daly, and Carsten (2014). For other scenarios, where braking or evasive maneuvers are required, the *Take-OverTime* can be assessed by defining thresholds for the steering wheel angle or braking pedal position. According to the studies of the author reported below and based on the evaluations of hundreds of take-over situations, the moment when the steering wheel angle exceeds 2 degrees or the braking pedal position exceeds 10%, is considered the *Take-OverTime* and interpreted to be the beginning of a conscious maneuver by the driver in order to react to the system limit. This distinction was adopted by other authors (cf. Zeeb, Buchner, & Schrauf, 2015; Louw, Merat, & Jamson, 2015; Kerschbaum et al., 2015) and can be considered the current state-of-the-art for take-over research in driving simulator studies. Whether these thresholds are useful for on-road studies is up for discussion. The thresholds

are usually exceeded by only a few milliseconds after the driver initiates the input, which means that this delay can be ignored when measuring *Take-OverTime* in a range of 2 to 4 seconds.

There are further useful measures of timing aspects of the take-over process, as listed by Gold, Lorenz, et al. (2013) and Lorenz, Kerschbaum, and Schumann (2014), including gazes to the mirrors, turning on the indicators, or the end of the maneuver, which are mentioned here but not considered further in this thesis.

#### 2.6.4.2 Quality Metrics of the Take-Over

There are several driving performance metrics that can be used to evaluate take-over quality. The relevance of the different measures depends on situational aspects and the required maneuver for handling the take-over scenario. If stabilizing the vehicle within the current lane is a sufficient response, measures such as the Standard Deviation of Lateral Position (STDLP) or the number of steering wheel reversals per minute could be assessed (Naujoks, Mai, & Neukum, 2014). The aim of this thesis is to measure and model human take-over performance. This is why more challenging scenarios were examined, which required brake reactions or evasive maneuvers. For the evaluation of take-over quality in these scenarios, the following measures were used.

- **Longitudinal Acceleration.** The *Long.Acc.* $\mathbf{a_{Long}}$ corresponds to the maximum absolute value of the acceleration in a longitudinal direction that occurred within the take-over situation. This could either be maximum positive accelerations or decelerations due to braking. In most of the cases, and especially in the scenarios implemented, a high longitudinal acceleration corresponds to intense braking for the purpose of gaining time before reaching the system limit or avoiding a collision with an obstacle ahead.
- **Lateral Acceleration.** The *Lat.Acc.* $\mathbf{a_{Lat}}$ is the maximum absolute value of accelerations transversely to the vehicle's longitudinal axis. High values indicate a sudden or dynamic evasive maneuver.

Both measures, *Long.Acc.* and *Lat.Acc.*, are based on the assumption that high accelerations indicate a less safe maneuvering and therefore a lower take-over quality, as these high accelerations are most likely the result of hectic driver input in a time-critical situation. Nevertheless, there might be situations where high accelerations could also indicate a good take-over quality, for example if strong braking or steering is the preferable maneuver.

- **Time To Collision.** The *TTC* is a surrogate safety metric and a common parameter for the criticality of traffic situations (ISO International Organization for Standardization, 2013-07-23). In take-over situations, it represents the time theoretically remaining until a potential collision with an obstacle, assuming constant speeds of the vehicle as well as of the obstacle. At the moment of the TOR, *TTC* equals the TB. For assessing take-over quality, the minimum Time To Collision (TTC) that occurred in a take-over situation is considered. Smaller numbers imply a more critical situation, as the remaining time until collision was shorter. A $TTC$ of 0 seconds corresponds to a collision. If the leading object is decelerating, the "Enhanced TTC" (Winner & Hakuli, 2015) can be used, as it takes into account the resulting non-linearity. For the scenarios considered in this thesis, differences of TTC and Enhanced TTC are marginal. The lead vehicle was stationary and solely the minimum of the TTC that occurred was used, leading to very similar results for both measures (Happee, Gold, Radlmayr, Hergeth, & Bengler, 2016).

- **Crash.** The variable $Crash$ $\mathbf{P_{Crash}}$ represents the frequency of crashes and results from the number of crashes that occurred divided by the total number of take-over situations considered. It is self-evident that a higher frequency of crashes indicates a lower take-over quality.

As already mentioned, there are several other measures such as the usage of acceleration potential (Gold, Dambock, Lorenz, & Bengler, 2013; Kerschbaum, Lorenz, & Bengler, 2014), overshoots and minimum distance to the obstacle (Happee et al., 2016), time to line crossing or STDLP (Naujoks et al., 2014). Nevertheless, this thesis focuses on the four above-mentioned parameters for assessing take-over quality, as they have proved to be valuable estimators in the time-critical scenarios considered. In any case, in the context of driving simulation experiments, caution should be used when drawing conclusions from absolute values of these parameters.

### 2.6.5 State of Take-Over Research

Triggered by increased capabilities of hard- and software, advanced digitization and expedited by huge development efforts of several international companies, the examination of human-automation interaction in ground transportation mainly evolved around the turn of the century. Previously, similar aspects were discussed in context of ADAS, e.g. mode confusion when using ACC systems (Larsson, 2010). In many respects, driving assistant systems research forms the basis for methods and approaches used to assess automated driving. However, with an increase of automated vehicle functions, effects arise that require new methods and metrics. Applied to human factors research for HAVs, different aspects can be transferred from other domains, whereas others demand new approaches.

As an example, research on human physiology, such as movement times, gaze behavior, reaction times, or thresholds of perception, form a valuable basis for HAD research. Standardized tasks that are used for driver distraction research can also be employed to generate reproducible experiments in HAVs. Methods such as driving simulators or questionnaire techniques are widely used and the design of the HMI in HAVs follows similar rules compared to current design standards.

On the other hand, the transferability of some cognitive models and models of interaction principles are yet to be verified. There are many automation effects known from other domains, such as aviation or production, which are likely to emerge when automating the driving task, but have never been considered in the context of road transportation research. Furthermore, many methods of evaluating controllability of assistant systems are not effective or too extensive when assessing the effects of introducing HAD (Winner

& Wachenfeld, 2013). Modeling driver performance in take-over scenarios is one way to face this issue.

### Interaction Design

In the *H-Mode* project, the arbitration of control between the human and the automated vehicle was compared to a metaphor derived from the interaction between human and horse while riding (Flemisch, 2003), and transitions and interactions between automated vehicles and the driver were examined. The interaction principle within *H-Mode* includes a dynamic distribution of control (shared control) between the driver and the automated vehicle (Bengler & Flemisch, 2011). Automation levels are, inspired by the horse metaphor, referred to as “manual”, “tight rein” and, “loose rein” (Geyer et al., 2014), and a shift between these levels was examined using different approaches, such as changing the automation mode by applying different grip forces (Damböck, Kienle, Bengler, & Bubb, 2011). Although later publications include the extension of the automation levels towards HAD with the driver being out of the loop (“secured rein”; Altendorf et al., 2015), the main focus of *H-Mode* were levels involving an active input of the driver with shared control.
In another project called *Conduct-by-Wire*, interaction between human and automation was implemented on a maneuver-based level. The automated system suggests maneuvers that are selected by the driver and executed by the automation (Flemisch, Bengler, Bubb, Winner, & Bruder, 2014; Franz, Kauer, Sebastian, & Hakuli, 2015). This approach of a maneuver-based driver input in HAVs is likely to emerge in future automated vehicles and is also present in the EU project *D3CoS*, where cooperation between human and machine is assessed in different domains. For road transportation, the driver-automation cooperation is assessed, e.g. when performing a lane change (Zimmermann & Bengler, 2013).
During the last few years, the EU project *HAVEit* pursued another approach of human-automation interaction. The interaction concept considered the driver state (Rauch, 2009) and adapted HMI parameters accordingly. TORs and other experiments of a different type were also considered (Flemisch et al., 2011). Additionally, the project tackled several functional aspects of HAD, such as sensor fusion, trajectory and maneuver planning (Flemisch et al., 2010).

The projects showed valuable approaches for facing necessary changes in human-machine interaction when introducing automated vehicle functions. Nevertheless, the expected design in future HAVs differs in many aspects, as vehicle functions evolve rather evolutionarily, and technological capabilities are still limited. Unlike the above-listed research projects, the interaction design of HAVs may not depict the paradigm change in road transportation appropriately. The take-over on emerging system limits in HAVs is no desired interaction principle, but an emerging necessity, resulting from the balancing of market demands, current technology capability and the legislative setting. It is an interim stage on the way to higher levels of automated driving, but remains a key aspect for the controllability assessment of HAD in the near future.

### Interface Design

In the context of automating the driving task, researchers have examined different new interface designs, in some cases replacing the established control elements. Input devices known from aviation, such as side sticks (Damböck et al., 2011) and a yoke, a two-axis input device (Kienle, 2015), were used. When retaining the current control elements, there are reasons for decoupling the steering wheel while driving in a highly automated mode. Kerschbaum et al. (2014) examined if a decoupled steering wheel and the phase of coupling back in influences the take-over. They did not find differences between the groups, indicating that it may be possible to decouple the steering wheel in some scenarios. Another concept of Kerschbaum et al. (2014) considered a steering wheel without spokes. This concept led to an improved take-over performance, which proves that adjustments or changes of input devices may become necessary, or that they will have supportive character at least.
Apart from changes to the control elements, other HMI adjustments could help to improve human-automation interaction (Beukel & Voort, 2011). The question arises how the driver could be supported in take-over experiments to shorten temporal aspects of the take-over and improve take-over quality. Different design implications apply for the HMI of HAVs with respect to improving the performance of the driver-vehicle-automation system (Beukel & Voort, 2014a, 2014b). The HMI design includes the design of the TOR. Lorenz et al. (2014) evaluated different representations of a safe corridor which the driver can use for the take-over maneuver and found implications on the maneuver type that participants selected as a response to the system limit. Several HMI concepts attempt to keep the driver aware of the situation and thus ready for taking over control. Lange, Maas, Albert, Siedersberger, and Bengler (2014) describe design considerations for desirable accelerations of maneuvers in HAVs to improve situation and state awareness. Blommer et al. (2015) have recently replicated parts of Carsten et al. (2012) and have implemented a scheduled driver engagement strategy.
A supportive HMI design that enables a decent level of mode awareness is important to reduce impairments due to mode confusion. Petermann and Schlag (2010) identified mode confusion as a relevant issue. They looked at users' expectations regarding the transitions and performed a Wizard of Oz study in a real vehicle, examining transitions between different automation levels. They further assessed mode confusion in a driving simulator experiment (Petermann & Kiss, 2010) and observed confusion of modes and misinterpretation of control arbitration. It is also evident that drivers who have previously driven in automated mode are less likely to intervene (in line with results of Waard et al. (1999) and Stanton et al. (2001)) and intervene later than participants who drive manually. In a study of Gold, Lorenz, Damböck and Bengler (2013), drivers were asked to monitor the scenery six seconds before an uncertain scenario. Two seconds later and therefore four seconds before reaching the system limit, the situation changed and required a take-over. In more than 20% of the situations, participants did not intervene, which leads to very risky situations of passing a pedestrian on the highway in a distance of approximately 20 cm. This, again, is an issue of mode confusion and should be addressed by an appropriate HMI design.
The design of the TOR itself was the focus of different studies. Although the representation of the TOR differs between the studies, the TOR is either presented visually

and acoustically (Gold, Lorenz, et al., 2013; Lorenz et al., 2014; Kerschbaum et al., 2014; Petermann-Stock, Hackenberg, Muhr, & Mergl, 2013; Zeeb et al., 2015) or solely acoustically (Beukel & Voort, 2013; Merat & Jamson, 2009). While Beukel and Voort (2014b) find negative implications of too much visual information within the TOR, there is clear evidence that exclusively visual TORs are not sufficient (Naujoks et al., 2014) and should be complemented with an auditory warning in order to ensure (fast) responses of the driver. There are currently no simulator studies known to the author considering other warning types in HAVs except for a theoretical approach of a vibrotactile interface (Petermeijer, Winter, & Bengler, 2015) and studies in the context of ADAS, for example on a tactile rear-end collision warning system (Scott & Gray, 2008).

As illustrated, there are lots of necessary design considerations when adapting the HMI to automated driving. While many principles can be transferred from former research, several questions will arise within the next few years, as the detailed design of the automated functions is not known yet and will significantly influence the interaction design parameters between the human and the automated system.

### Take-Over Performance

Take-over situations can occur in a variety of different settings, with different driver states, skills and experience. There are lots of potential factors which probably influence the take-over performance and which have to be examined in order to obtain a holistic picture of take-overs in HAVs. Results regarding different aspects of take-over research are based on system-initiated take-overs, triggered by a TOR. Failures of the automation, as considered in several publications (e.g. Beller, Heesen, & Vollrath, 2013; Shen & Neyens, 2014; Strand et al., 2014; Levitan, Golembiewski, & Bloomfield, 1998; Toffetti et al., 2009) will not be addressed further in this thesis.
Only in the last few years has the focus shifted to transitions between an automated system which executes the entire driving task, back to the driver retaking the vehicle guidance. Several research groups have mostly performed driving simulator studies, assessing the take-over in HAVs. There is evidence that automating the driving task impairs the driver's performance. Young and Stanton (2007a) have measured longer brake reaction times under automated conditions compared to manual driving, which could be caused by a reduction of workload due to automation (Stanton et al., 2001), leading to low levels of activation, which can induce slower reactions (Welford et al., 1980). Merat and Jamson (2009) examined different aspects of the take-over. They found later responses to the TORs when compared to manual driving. Apart from slower reactions, increased accelerations are observed when reacting to a system limit (Louw et al., 2015). Currently, the main research focus is to develop an understanding of factors that influence take-over performance, such as the Time Budget (TB), non-driving-related tasks, driver's age or other factors such as fatigue, trust and training, which are briefly outlined below.

The TB the driver needs to react appropriately to the TOR was subject to several studies. On the one hand, the TB is important in order to validate if those take-overs can reasonably be demanded of the driver, on the other hand, to find out how much time the automation has to provide, with implications on required sensor ranges and reliability.

In a driving simulator study, Damböck, Farid, Tönert, and Bengler (2012) compared TBs of four, six, and eight seconds. Only with eight seconds did they not find significant differences regarding successful maneuvers compared to participants driving manually. Nevertheless, take-over quality was only evaluated on the level of a binary success variable, without considering additional quality aspects such as accelerations or TTC. Damböck also found that smaller TBs increase errors and that the TB influences the take-over process, for example extending the time for repositioning the hands on the steering wheel (*HandsOnTime*) (Damböck, 2013). Beukel and Voort (2013) tested very small TBs in typical rear-end near-crash situations. They offered TBs between 1.5 and 2.8 seconds for reacting to a braking lead vehicle, which led to accidents in 47.5% and 12.5% of the situations, respectively, indicating that transition, even in simple, straightforward brake situations, requires several seconds, which is in line with the results of Damböck et al. (2012). Participants in the study of Zeeb et al. (2015) had slightly higher TBs (4.9 to 6.6 seconds), but similar accident rates (15 to 45%). This can be attributed to more complex take-over scenarios, again including a near rear-end crash situation, but with vehicles occupying the neighboring lane, preventing an evasive maneuver.
Merat, Jamson, Lai, and Carsten (2012) and Petermann-Stock et al. (2013) followed a different approach. They presented rather uncritical scenarios and measured the take-over time. Merat et al. (2012) issued a warning 48 seconds before a system limit and did not find differences in vehicle speeds and time of lane change between manually driving participants and those experiencing automated driving. In the study of Petermann-Stock et al. (2013) 70 of 72 participants managed to take over vehicle control within ten seconds (m=3.2s; max=8.8s). However, while this approach of presenting uncritical scenarios is valuable for assessing take-over performance at the end of the automation scenario or other map-based system limits, for example, conclusions on the minimally required TB should not be drawn without cautious consideration.

Various non-driving-related tasks are used for different purposes in HAD research. On the one hand, engagement in non-driving-related tasks can be expected to influence the take-over performance; on the other hand, non-driving-related tasks are used to distract the driver and generate reproducible results, which differ from results of partially automated systems, where the driver should be attentive and aware of the situation. As a stronger engagement in non-driving-related tasks is present when driving in automated mode (Jamson, Merat, Carsten, & Lai, 2013), less attention is paid to the situation on the road (Carsten et al., 2012), and participants who tend to be distracted more easily perform worse and possibly react inappropriately in take-over situations (Zeeb et al., 2015; Petermann-Stock et al., 2013), a consideration of non-driving-related tasks in HAD research is necessary.
Results of an expert analysis show that several tasks are imaginable while driving in automated mode, including changing clothes or shaving (Petermann-Stock et al., 2013). The effect on take-over performance of some of these tasks has already been examined, for example texting and browsing the internet (Zeeb et al., 2015), the verbal "20 Questions Task" (Merat et al., 2012), cell phone use (Neubauer, Matthews, & Saxby, 2012), interaction with the in-vehicle information system (Toffetti et al., 2009), tracking tasks (Damböck et al., 2012), watching videos, or listening to the radio (Blommer et al., 2015).
Within this context, Neubauer et al. (2012) compared a group of participants driving in

automated mode who were engaged in a phone call with participants driving without an additional task and measured brake reaction times. Remarkably, they found quicker reactions in the group engaged in a phone call. This could be explained by higher levels of activation in the phone-group, enabling fast reactions.
While the results provide evidence that non-driving-related tasks have an effect (positive or negative) on the take-over in HAVs, the possibility of a successful integration in an overall context, outlining the relation among the tasks and comparing them to other factors, is limited.

Other factors like age, fatigue, and trust have been considered as influencing factors as well. In a driving simulator study, take-over times were measured in dependence of driver's age (Petermann-Stock et al., 2013). Although they had two groups of 36 participants each, with a mean age of 34 years and 60 years, respectively, they did not find age-related effects regarding the take-over time. This might be caused by rather uncritical take-over scenarios, with an extended TB, not requiring an immediate take-over. The results are in line with findings concerning age effects when responding to forward collision warnings (Kramer, Cassavaugh, Horrey, Becic, & Mayhugh, 2007). Regarding driver's fatigue, results indicate that fatigue delays braking response in take-over scenarios (Neubauer et al., 2012). Additionally, other dependent variables such as trust in automation (Beukel & Voort, 2014a; Gold, Körber, Hohenberger, Lechner, & Bengler, 2015) and situation awareness (Beukel & Voort, 2014b) are being assessed and a negative influence of trust on driver's performance was found in the context of system failures (Shen & Neyens, 2014).
It is known that behavioral adaptation to support systems changes over time (Markkula, Benderius, Wolff, & Wahde, 2012). Several studies indicate that learning effects are present (Gold & Bengler, 2014; Beukel & Voort, 2014a; Carsten et al., 2012; Petermann-Stock et al., 2013). Participants repeatedly experiencing take-over situations get trained for taking over vehicle control and show improved take-over performance, especially if the scenarios are very similar, an aspect that has to be considered when designing take-over experiments, especially as previously instructing the participants can have similar effects on the performance (Hergeth, Lorenz, & Krems, 2016).

Research shows many different relevant aspects when assessing take-over performance in HAVs and has found important issues that arise with an automation of the driving task. Most of the experiments mentioned considered one or two possible influencing factors at a time. However, while the effects found are of specific value, the experiments allow a rather implicit view and hardly enable a merging of results into a holistic picture.

## 2.7 Modeling of Take-Over Situations

There is an urgent need for modeling take-overs in HAVs. Considering that these systems will be almost flawless, the transition from automated driving back to the driver is probably the most critical safety aspect. Simultaneously, the effort involved in examining take-over scenarios is extensive, as a huge variety of situations, drivers, states, and activities as well as system specifications have to be considered for the development and safety assessment of HAD. Covering all controllability aspects by implementing experiments in driving simulators and on-road is not feasible within a limited time frame and with limited resources, whereas different methods are needed in order to assess the safety of HAVs. The timely modeling of take-over scenarios can help to identify and quantify critical aspects and influencing factors on the take-over performance and thus reduce the necessary experimental effort. Modeling, based on a series of experiments, allows a deeper understanding of the take-over compared to a consideration of separate experiments. By enabling a quantification of influencing parameters, potentials to support and improve the take-over can be identified and thus lead to increased take-over performance and safer vehicle automation. Automated driving on highways is considered to be the initial use case of HAVs. For modeling the take-over and conducting experiments within this thesis, situations have been limited to driving on a highway in HAVs. Here, system limits are very likely to be ahead of the vehicle. That is why experiments and modeling are focused on system limits on the current lane of the automated vehicle, represented by a stationary vehicle. The following modeling approaches are selected accordingly to model near-crash situations focused on rear-end collisions. Different driver models are discussed and in addition, further modeling approaches are considered to satisfy aspects specific for drivers' behavior in HAVs.

### 2.7.1 Modeling Driver Behavior in Near-Crash Situations

Assuming that a take-over in a HAV is a scenario with an obstacle ahead and the take-over time is limited to a few seconds due to sensor range, these scenarios resemble situations in manual driving with a lead vehicle that suddenly stops or brakes. There are several authors who model these scenarios with regard to brake reactions (Subsection 2.7.1.1) as well as steering maneuvers (Subsection 2.7.1.2).

#### 2.7.1.1 Models for Brake-Reactions

Just like with take-over behavior, models for timing and quality aspects of brake reactions exist. For the timing of a brake reaction in manual driving, a popular model was introduced by Lee (1976), assuming that the brake reaction correlates with "the rate of dilation of the retinal image of the obstacle" (Lee, 1976, p. 441). The inverse of the rate of dilation ($\tau(t)$) specifies the TTC. Following the model, drivers brake as soon as $\tau$ exceeds a certain margin value $\tau_m$. For different constant decelerations and vehicle speeds, $\tau_m$ can be derived from Figure 2.11.

Kiefer, LeBlanc, and Flannagan (2005) also correlate the timing of brake reaction with the inverse TTC, based on 3,536 brake reactions while approaching a surrogate target lead vehicle. For stationary obstacles, the number of brake reactions is lower (54 trials with 30 and 69 mph), but allows expressive conclusions. For the stationary lead vehicle, the authors set up Equation 2.2, while $x$ is a variable forced to map onto a logistic Equation 2.1. The resulting $p$ is the probability "that the existing kinematic conditions are a hard (rather than a normal) braking" (Kiefer et al., 2005, p. 299). The authors suggest values of $p = .75$ and $p = .95$. Solving the equations for TTC leads to Equation 2.3. A hypothetical vehicle speed of 120 km/h (74.56 mph) results in TTC values of 3.91

($p = .75$) and 3.01 seconds ($p = .95$), respectively, for the timing of the brake reaction to a stationary lead vehicle. This corresponds to stronger braking reactions of about 0.6 g to 0.8 g in the model of Lee (1976).

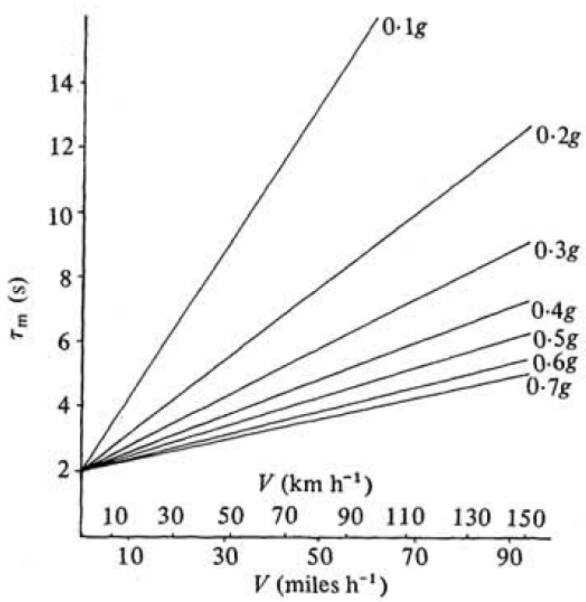



Figure 2.11: Thresholds of $\tau_m$ for brake-reaction to stationary obstacles (Lee, 1976). According to the model, drivers brake as soon as the inverse of the rate of dilation exceeds $\tau_m$.

$$p = 1/(1 + e^{-x}) \tag{2.1}$$

$$x = -9.073 + 24.225(\frac{1}{TTC}) + 0.0534 * V_{vehicle} \tag{2.2}$$

$$TTC = \frac{24.225}{-\ln(\frac{1}{p-1}) + 9.073 - 0.0534 * (V_{vehicle})} \tag{2.3}$$

Another common "follow-the-leader model" was published by Gazis, Herman, and Rothery (1961) and is called the GHR-model (Equation 2.4). While $x$ represents the position of the following and leading vehicle respectively, $T$ is the response time of the driver and $\lambda$ is what is referred to as "sensitivity", which can either be set to constant or as a function of the spacing $\lambda = f(x_{leading} - x_{following})$. Different driver models build upon this approach (Markkula et al., 2012), such as the model of Gipps (1981)(Equation 2.5), which is cited particularly often. According to the model of Gazis et al. (1961), $b$ is the "most severe braking that the driver wishes to undertake" (Gipps, 1981, p. 106) and $s$ the dimension of the vehicle.

$$\ddot{x}_{following}(t + T) = \lambda[\dot{x}_{leading}(t) - \dot{x}_{following}(t)] \tag{2.4}$$

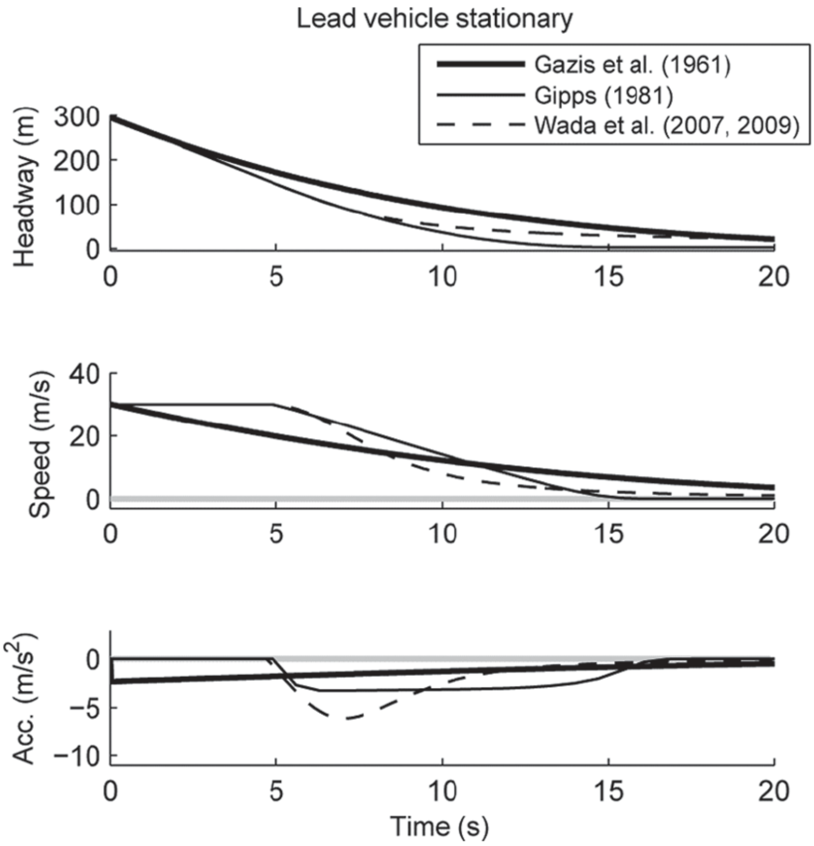



Figure 2.12: Examples for driver braking models with LVS (Markkula et al., 2012).

$$\dot{x}_f(t+T) \leq b_f T + \sqrt{b_f^2 T^2 - b_f(2[\Delta x(t) - s_l] - \dot{x}_f(t)T - \frac{\dot{x}_l(t)^2}{b_l}} \tag{2.5}$$

In an example, Markkula et al. (2012), who revised models for driver behavior in near-crash situations, compared the models for Lead Vehicle Stationary (LVS) and another model of Wada et al. (2007) (cf. Figure 2.12). To model vehicle speed and accelerations, the headway to the stopped vehicle was set to 300 meters and the speed to 30 m/s. While braking starts immediately in the model of Gazis et al. (1961), the brake response in the model of Gipps (1981) is delayed and starts at about 5 seconds. This corresponds to a position 150 meters ahead of the stationary vehicle and therefore to a TTC of 5 seconds, a faster response compared to the above mentioned models of Kiefer et al. (2005) and Lee (1976). Nevertheless, as with the majority of the models, variables are present that can be adapted to different drivers and situations to increase the model fit. This means that the model could be applied to take-over behavior by increasing the response time $T$, modeling the delayed reaction due to non-driving-related tasks and the time needed to refocus on the driving task.

#### 2.7.1.2 Models for Steering Maneuvers

Just like for brake reactions, several authors have proposed models for lane change maneuvers for the purpose of crash avoidance. The models are based on path following control theory and need a desired path as input for the modeling. Markkula et al. (2012) compared different models for a 20-meter single lane change at 20 m/s (cf. Figure 2.13). As trajectory modeling is not desired for the purpose of take-over modeling in this thesis, these models are not presented in detail. The paper of Markkula et al. (2012) is recommended, however, to gain a detailed insight.

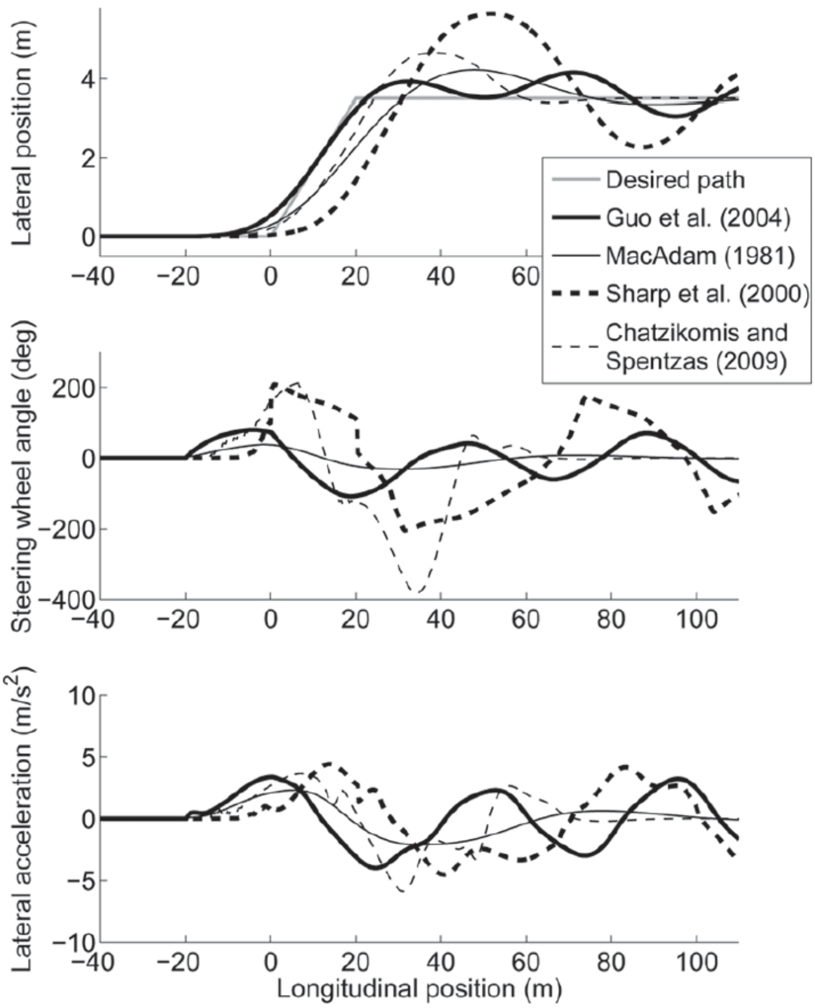



Figure 2.13: Examples for lane change models (Markkula et al., 2012).

### 2.7.2 Modular Additive System Modeling

A different approach for modeling take-over behavior consists of dividing the take-over into segments, which represent a sequence of relevant actions when taking over vehicle control. Segments could be the driver's reaction time, motoric allocation, cognitive take-over, and response execution. Influences on these segments due to automation or non-driving-related tasks could be measured and effects on the take-over performance assessed. By a modular additive merging of the different segments, a prediction of take-over performance could be made. The modular additive system modeling approach implicates that the take-overs can be modeled as a linear, sequential process, questioning validity, as some aspects of the take-over are likely to be rather parallel (cf. Figure 2.10).

Figure 2.14 depicts an example for such a modular additive system model, based on literature and estimations. The model serves as an example and does not include further scientific claims. Values for the simple reaction time, influences of the non-driving-related task, the gaze reaction, and motoric movements were derived from relevant literature. A quantification of the time required to regain cognitive resources for the take-over will still have to follow. The process of information perception was approximated by the accompanying visual scanning. In a similar way, information processing and the effect of training was assessed by applying the cognition models for choice reactions (Hicks Law; Card, Moran, & Newell, 1986) and the Power Law of Practice (Card et al., 1986). For predicting a take-over, times can easily be derived by a horizontal sum-up of the appropriate cells of each column. In accordance with the take-over procedure in Figure 2.10, the model supplies relevant timing aspects such as the *GazeReactionTime*, the time until the gaze reaches the scenery (Gaze on Scenery), the time until the driver has returned to his driving position (Hands-On Time), the *Take-OverTime*, or the time until the maneuver is finished.

This model, as shown in Figure 2.14, only considers timing aspects of the take-over. Take-over quality could be modeled accordingly or in dependence of the timing aspects derived from the model. The latter would describe variables such as the accelerations occurred as a result of time pressure in the situations, which is induced by the TB and the length of the process, modeled by the modular additive system approach. It could be claimed that a lack of time will lead to increased accelerations and lower TTC values. If the resulting time for the take-over is close to the available TB, maneuvering can be expected to be rather intense, whereas, if the TB is significantly larger, maneuvering would probably be smoother, inducing lower accelerations and higher TTC values. However, the capability to draw conclusions on the take-over quality is rather limited.

There are additional aspects which are not represented in the model, but which literature indicates to have an effect on the take-over. Fatigue, for example, influences the reaction time (Welford et al., 1980); so does the time of day (Höhne, 1974), the age of the driver (Cantin et al., 2009; Höhne, 1974; Kováč, 1969), gender (Welford et al., 1980), the driver's expectation regarding the warning (Delaigue & Eskandarian, 2004), or the frequency of the warning (Krinchik, 1969).

Take-Over Time → Maneuver Time →
Hands-On Time →
Gaze on Scenery →
Gaze Reaction Time →

| Reaction | | Gaze Reaction Time | Saccade | Motoric | Cognitive Take-Over | | | Cognitive Take-Over | Response | |
|---|---|---|---|---|---|---|---|---|---|---|
| **Reaction time until first response to the TOR can be observed.** **Simple Reaction** | **Task** | | **Visual reorient. - Saccade to the scenery** | **Motoric reorientation to the driving tasks.** | **Regaining cognitive resources for the take-over.** | **Information perception. Assessed via number of relevant objects, saccades and fixation times: $t_{per}=n*(D_0+d*A+f)$. Assuming $D_0$=21ms , d=2.2ms, f=0.3s, A=10°.** | **Information processing and response selection. Based on Hicks Law: $t=I_c*\log_2(n+1)$. Assuming $I_c$=150ms.** | | **Training. Based on Power Law of Practice: $T_n = T_1 \cdot n^{-r}$. Assuming: $T_1=t_{cognitive}$, r=0.4** | **Response execution.** |
| Auditory TOR (reference): $t_{sr}=t_{aud}=0.5$ s | Without task (reference): $t_{task}=t_{ref}=0.0$ s | $t_{reaction} = t_{sr} + t_{task}$ | Eyes on road (reference): $t_{gaze}$=0.0 s | Driver in driving position (reference): $t_{mot}$=0.0 s | Low cognitive demand (cd) due to task (reference): $t_{rcr}= f_{(cd=low)}$ = 0.0 s | Low number of relevant objects (n=1): $t_{per}$=0.3 s | Stabilization only (n=1): $t_{pro}$=0.15 | $t_{cognitive} = t_{reaction} + t_{gaze} + t_{mot} + t_{rcr} + t_{per} + t_{pro}$ | First take-over experienced (n=1): $t_{tra}=t_{cognitive}$ | Stabilization (reference): $t_{res}$=0.0 s |
| Haptic TOR: $t_{sr}=t_{hap}$= 0.4 s | Task with medium cogn. distraction: $t_{task}=t_{ref}+t_{mcog}$= 0.0 s + 0.08 s | | Eyes off road: $t_{gaze}=t_{EOR}$= 0.48s | Feeds off pedals: $t_{mot}=t_{foff}$= 0.5s | Medium cd due to task: $t_{rcr}= f_{(cd=med)}$ [s] | Medium number of relevant objects (n=3): $t_{per}$=1.0 s | Guidance and stabilization (n=2): $t_{pro}$=0.24 | | Second take-over experienced (n=2): $t_{tra}$= - $t_{cognitive}*2^{-0.4}$ | Braking to full stop: $t_{res}$=v/a. With: v = vehicle velocity a = deceleration |
| Visual (driver vis. attentive) : $t_{sr}=t_{vis}$= 0.6s >10° off sight-line: $t_{vis}$=0.7s | Task with intense cogn. distraction: $t_{task}=t_{ref}+t_{icog}$= 0.0 s + 0.3 s | | | Hands off steering wheel: $t_{mot}=t_{hoff}$=0.7s | High cd due to task: $t_{rcr}= f_{(cd=high)}$ [s] | High number of relevant objects (n=5): $t_{per}$=1.7 s | Navigation, guidance and stabilization (n=3): $t_{pro}$=0.30 | | $n^{th}$ take-over experienced: $t_{tra}$= - $t_{cognitive}*n^{-0.4}$ | Lane change (until lane is left): $t_{res}$= approx. 3s |
| ... | ... | | | ... | ... | ... | ... | | | ... |

Figure 2.14: Example of a modular additive system modeling timing aspects of the take-over. Sources: Auditory Reaction Time $t_{aud}$ (Burckhardt, 1985), Haptic Reaction Time $t_{hap}$ (Scott & Gray, 2008), Visual Reaction Time $t_{vis}$ (Scott & Gray, 2008), $> 10°offsightline : t_{vis}$ (Höhne, 1974), Medium Cognitive Distraction $t_{mcog}$ (Patten et al., 2004), Intense Cognitive Distraction $t_{icog}$ (Makishita & Matsunaga, 2008), EyesOnRoad Time $t_{EOR}$ (Burckhardt, 1985), Movement Times $t_{foff}$ & $t_{hoff}$ (Damböck, 2013), Information Processing Formula derived from (Schweigert, 2003), Hicks Law, Power Law of Practice and associated coefficients (Card et al., 1986), Timing of a lane change (Salvucci & Liu, 2002).

### 2.7.3 Artificial Neural Networks

An Artificial Neural Network (ANN) and the regression described below are mathematical methods used to model different types of systems. Both try to describe the correlation of input (predictors) and output (response) variables by minimizing cost functions. The ANN is inspired by neuronal brain cells. In a neuron, several inputs of other neurons are summed up, and if the sum exceeds a threshold, the neuron itself emits a signal to subsequent neurons.

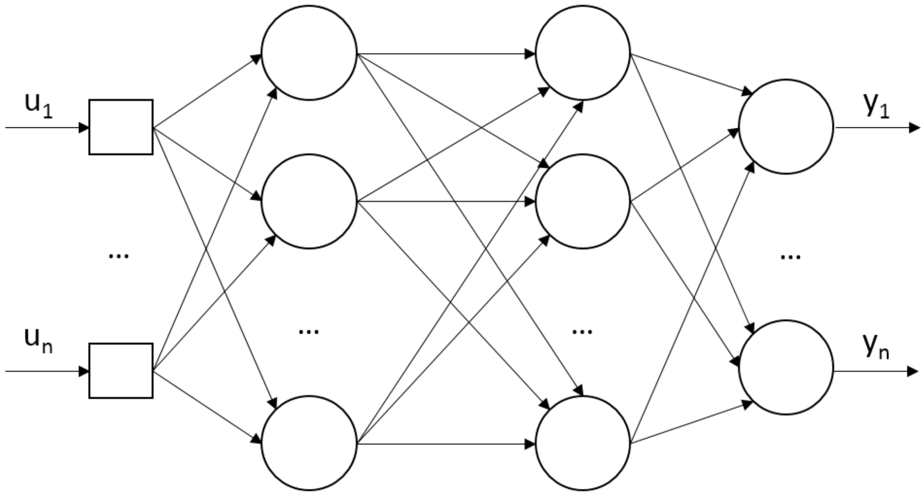



Figure 2.15: Artificial Neural Network containing two hidden layers.

Figure 2.15 shows a feed-forward ANN. Such networks have an input and an output layer and at least one “hidden layer” in between, consisting of what is referred to as knots or neurons. In Figure 2.15, a feed-forward network with two hidden layers is depicted exemplarily. Each input parameter $u$ serves as an input for the first hidden layer. Furthermore, the inputs of the knots are weighted by a factor $w$. Within the knots, the output is calculated by the use of different functions and under consideration of the weighted input. Subsequently, the outputs of the first hidden layer serve as input for the second hidden layer. On the right side, outputs of the last hidden layer are summed up within the output layer. ANN that feed the output of a knot back to previous layers are called recurrent networks and used, for example, for modeling dynamic systems. In order to model a system, the ANN is trained by a data-set of input and output parameters. In an iterative process, weights are adjusted to reduce the prediction error by the use of different cost functions. There are several algorithms and different methods to train an ANN. Commonly, the data-set is divided in order to use one part for training and the other part for validating the model. By the use of ANNs, very complex systems can be modeled without the need for assumptions or extended knowledge of the systems' properties. They can also be applied to model human behavior, and there are different authors who model driving behavior by the use of ANNs, for example for car-following behavior (Colombaroni & Fusco, 2014) or for maneuvers that combine longitudinal and lateral control (Wei, Ross, Varisco, Krief, & Ferrari, 2013). Panwai and Dia (2007) showed that ANNs enable significant improvements compared to various other car-following models, such as the previously mentioned GHR Model. Prakash, Patil, and Kalyani

(2013) reported similar findings. They developed a driver model and found that “the ANN driver model predicts vehicle performance better than PID-based driver models” (Prakash et al., 2013, p. 1). ANNs are further considered in different contexts of road transportation research, for example for driver drowsiness (Daza et al., 2011; Sayed & Eskandarian, 2001) or fatigue detection (Chang & Yi-Ru Chen, 2014; Liu et al., 2014), for identifying the driver based on his driving profile (Wahab, Chai Quek, Chin Keong Tan, & Takeda, 2009), predicting drivers’ route choice (Kim & Kim, 2011), or for developing steering algorithms (Darter & Gordon, 2005). ANNs are able to reproduce almost any behavior, however, interpretation afterwards is difficult. The complexity of ANNs makes it difficult to draw conclusions regarding individual influencing factors, and knowledge about coherence and causalities is limited.

### 2.7.4 Regression Analysis

By the use of regression analysis, mathematical relationships between several predictor (input) parameters and a response (output) parameter can be estimated based on a mathematical model. The fitted model that results from this can be used for predicting outputs based on a set of weighted predictors and, furthermore, the regression analysis can identify the contribution of the different predictors to the response variable. An example is the general linear regression, shown in Equation 2.6. The output $y$ is described as a linear combination of the input variables $x_i$ multiplied with the coefficients $\beta_i$.

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + ... + \beta_i x_i + \epsilon \tag{2.6}$$

The regression estimates $\beta_i$ by the use of different optimization functions. The most common method is calculating $\beta_i$ by minimizing the sum of the squared residuals (Ordinary Least Squares (OLS)), reducing the distance between measures and calculated values. The regression equations can also contain non-linear input parameters and variables such as exponential functions requiring non-linear regressions (cf. Equation 2.7).

$$y = \beta_0 + \beta_1 x_1 + \beta_2(\beta_3 + x_2)^2 + ... + \beta_i x_i + \epsilon \tag{2.7}$$

A wide range of regression variants exists, for example logistic regressions for predicting discrete response variables and mixed-effect models that consider random parameters. In general, regression methods assume a normal distribution of the response, which is why methods exist to address violations of this assumption. The robust regression addresses an increased occurrence of outliers, and the generalized linear models can consider distributions that differ from the Gaussian distribution.

Similar to ANNs, regression models are a well-established method in human factors and road transportation research. They are used for modeling rear-end accidents (Yan, Radwan, & Abdel-Aty, 2005), finding covariates leading to accidents (Famoye, Wulu, & Singh, 2004), modeling acceleration and lane changing behavior (Ahmed, 1999), driver distraction (Weller & Schlag, 2009), or drowsiness (Chin-Teng et al., 2005).

Regression methods have a wide area of application and are able to accurately model the output of various systems. In order to do so, regressions require a basic understanding of the underlying coherence of predictors to generate valid regression equations. Accuracy can further be improved by considering assumptions and restrict the variables' range. In return, regressions reveal the correlation between the predictors and make it possible to identify the main factors that determine a model's output. The resulting regressions support the utilization of results, as equations and coefficients can be described easily, whereas an ANN would require the exchange of model-files and additional source code.

# 3 Take-Over Experiments and Model Selection

This thesis aims to model the take-over in a Highly Automated Vehicle (HAV). Although several studies have already been conducted as described in Subsection 2.6.5, the available data is not adequate for modeling take-over performance. Only a few influencing factors have been considered in particular scenarios, partially difficult to compare among themselves. In order to build an adequate model, it is necessary to identify all major factors influencing the take-over. Although the reported studies indicate some parameters, several driving-simulator studies were conducted and published during the last few years in order to gain a better understanding of the take-over in HAVs and enable a profound modeling. Some of these studies were conducted previously to the studies reported in Subsection 2.6.5 and have thus influenced the field of research in question and the current state-of-the-art of take-over experiments.

## 3.1 Selection of Influencing Factors

For the experiments, seven explanatory variables were selected as the possibly most relevant influencing factors of take-over performance. The selection was based on the above-mentioned take-over research (cf. Subsection 2.6.5), although the number of relevant publications regarding take-over in HAVs was small when the experiments were planned. The Time Budget (TB) was identified as a main relevant factor, because the TB limits the time the driver has to handle the take-over. This restriction of the TB determines the quality of the driver's activities, defined by the (limited) capability of the driver in the available time. Therefore, as the driver has limited resources (cf. Wickens et al., 2013) and the required driver response remains similar, a limited **time budget** is expected to reduce the driver's performance.

This goes along with the idea of presenting an **automated braking** function in order to prolong the TB and thus improve take-over performance, which is why automated braking was selected as a second factor.

Another selected factor is **traffic density**. Increased traffic density involves a higher number of relevant objects that have to be perceived, a time-consuming process, not only due to limited resources. Increasing traffic density implies a raise of the take-over scenario's complexity and is therefore a suitable method to vary the demand of the scenario.

If these resources are additionally occupied by preceding **non-driving-related tasks**, performance is expected to further decrease. This is the main reason for taking non-driving-related tasks into account; however, the possible change in arousal (cf. Teigen, 1994) also justifies a closer look at this factor.

The experience of a take-over may change the expectation regarding further take-overs and influence the driver's behavior. Additionally, behavioral adaption is likely to occur (cf. Rasmussen, 1983), and the driver's behavior may change from knowledge-based to rule-based behavior during the first take-overs, referred to as the factor **Repetition** in the experiments.

During the experiments, stationary vehicles had to be passed. The trajectory planning for this maneuver represents rule-based behavior. It was expected that there are common rules to pass stationary vehicles in the right lane but not in the left lane, as German drivers are only allowed to pass on the left side in regular traffic conditions. In addition, a stationary vehicle in the center lane increases possible options and may therefore increase the choice reaction time (cf. Uncertainty Principle Card, Moran, & Newell, 1983), whereas the take-over situations took place in different **lanes**.
The last explanatory variable that was considered is drivers' **age**. Although the study of Petermann-Stock et al. (2013) did not reveal age-related effects on take-over performance, there might be an effect when designing take-over in a more time-critical and thus more challenging way. Due to economic limitations, no other factors could be considered, although there might be more possible explanatory variables that might make a valuable contribution to clarifying variance and understanding the take-over in HAVs.

## 3.2 General Experimental Design

The experiments conducted focus on measuring timing aspects of the take-over as well as take-over quality, as both, times and quality, are the focus of posterior modeling. Considerable effort was expended to clarify different aspects of the take-over; however, constraints were necessary, as this work cannot cover all possible aspects. For this reason, the automation scenario was limited to automated highway driving. In this setting, the relative speeds of relevant road users are comparatively low and the variety of road users is limited. Furthermore, compared to urban traffic, object density on highways is lower and no close passing of contraflow traffic takes place. The maximum speed of the automation and the speed of the vehicle when entering the take-over scenario was set to 120 km/h (approx. 75 mph) in all studies. In addition, the studies are limited to a certain class of system limits, represented by broken down vehicles in the current participant's lane. This type of near rear-end collision, or more generally any type of stationary object blocking a lane (LVS), seemed to be the most relevant take-over scenario (Najm, Smith, & Yanagisawa, 2007). The vehicle moves in its lane and system limits are therefore likely to occur on this path. Furthermore, when considering crashes between two vehicles, "lead vehicles stopped" is currently the most relevant cause for light vehicle crashes (Najm et al., 2007). As described in Subsection 2.6.2, capabilities of future HAVs may vary and the scenarios examined are likely to be handled by the automation without the necessity of a take-over, or at least by a degradation to AEB functionality and thus collision avoidance via braking maneuvers. Nevertheless, the implemented take-overs are exemplary and served to measure take-over performance under time pressure in order to evaluate human capabilities in such situations. Due to the limited TB available and the imminent collision with the obstacle, the scenario is very demanding, enabling an observation of drivers' maximum performance and thus effects of the selected influencing factors. Additionally, the scenario and method can be described unambiguously and enhance the reproducibility of the experiments, which supports the deployment of a common methodology for the take-over in HAVs.

To secure the desired TB, the system limit must not be detectable prior to the TOR, which is why all studies include a vehicle which conceals the system limit and changes lane just in the moment of the TOR, or the system limit suddenly appears in the simulation environment. The latter prevents influencing the participants' maneuver selection, as otherwise they might be likely to simply follow the lead vehicle which changes the lane, without considering other options. The TOR was implemented as an audio-visual warning, including a red icon indicating the necessity for taking over vehicle control and an urgent sinusoidal double beep (approx. 2800 Hz, 75 dB). The auditory part is essential, as a large share of the participants was visually distracted and the detection probability for visual icons was rather low. In Experiment 5 (Subsection 3.3.5), the auditory double beep was replaced by voice giving the instructions "Brake!", "Left!", and "Right!" (in German), and the visual icon was replaced by a stop sign and two arrows pointing to the left and the right lane according to the voice command. This was implemented in order to support the decision-making process and represent an advanced HMI, but is not further considered within the modeling. Parts of the experiments were conducted in the dynamic driving simulator of the BMW Group Research and Technology and parts in the fix-based driving simulator at the Institute of Ergonomics of the Technical University of Munich. Both driving simulators are very high-fidelity and include a full vehicle mockup, surrounded by several projectors enabling a front view of about 200 degrees and the representation of all driving mirrors. The dynamic driving simulator has the additional capability of representing accelerations and therefore kinesthetic stimulation by the use of a hexapod allowing small lateral movements and rotations around the three axes. Accelerations of up to about 2.5 $m/s^2$ can be displayed by moving the mock-up.

## 3.3 Summary of Experiments Conducted

Six experiments were conducted to measure the influence of the seven selected factors *TimeBudget*, *AutoBrake*, *TrafficDensity*, *Load* due to non-driving-related tasks, *Repetition*, *Lane* and drivers' *Age*. Table 3.1 summarizes the experiments and lists the various factors. The variables which are in the focus of the studies are marked in bold. Variables that varied between subjects are presented in separate lines, variables that varied within subject are given in one line. The different experiments are published in English in either journals or conference proceedings and are therefore only briefly described in this thesis. Please refer to the publications for detailed results and further information on the experimental setup, methods, and hypotheses.

Table 3.1: Overview of take-over experiments conducted.

| Experiment | Participants | SAE-Level | TB[1] | AB[2] | TD[3] | NDRT[4] | REP[5] | Lane[6] | Age |
|---|---|---|---|---|---|---|---|---|---|
| Experiment 1 | n=15 | **3** | **5** | - | 0 | SuRT | 1 | R | m=28y |
| | n=13 | **3** | **7** | - | 0 | SuRT | 1 | R | |
| | n=5 | **0** | **5** | - | 0 | - | 1 | R | |
| | n=8 | **0** | **7** | - | 0 | - | 1 | R | |
| Experiment 2 | n=16 | 3 | 5 | **-** | **0,30** | SuRT | 4 | **L**/**C**/**R** | |
| | n=16 | 3 | 5 | **3.5** | **0,30** | SuRT | 4 | **L**/**C**/**R** | m=31y |
| | n=16 | 3 | 5 | **5.0** | **0,30** | SuRT | 4 | **L**/**C**/**R** | |
| Experiment 3 | n=16 | **3** | 7 | - | **0,30** | **SuRT** | 4 | **L**/**C**/**R** | m=34y |
| | n=16 | **3** | 7 | - | **0,30** | **2-Back** | 4 | **L**/**C**/**R** | |
| | n=16 | **0** | 7 | - | **0,30** | **2-Back** | 4 | **L**/**C**/**R** | |
| Experiment 4 | n=35 | 3 | 7 | - | **0,10,20** | **20-Questions** | 3 | L/C/R | m=45y |
| | n=36 | 3 | 7 | - | **0,10,20** | **None** | 3 | L/C/R | |
| Experiment 5 | n=24 | 3 | 7.8 | - | 0 | **SuRT,Text,Manual,2-Back** | **12** | C | m=28y |
| Experiment 6 | n=36 | 3 | 7 | - | 0,10,20 | **20-Questions,None** | **3** | L/C/R | **m=23y** |
| | n=35 | 3 | 7 | - | 0,10,20 | **20-Questions,None** | **3** | L/C/R | **m=67y** |

[1]TB = Time Budget [$s$]
[2]AB = Automated Braking [$m/s^2$]
[3]TD = Traffic Density [$vehicles/km$]
[4]NDRT = Non-Driving Related Task
[5]REP = Repetitions (number of take-overs experienced)
[6]Lane: Left (L), Center (C), Right (R)

### 3.3.1 Experiment 1: Comparison of Different Time Budgets

The first experiment[1] (Gold, Dambock, et al., 2013), conducted in the dynamic driving simulator, compared TBs of 5 and 7 seconds and considered manual drivers as a reference condition. In total, 49 drivers participated in the study, whereof 41 could be considered in the evaluation. Thirteen of these were manual reference drivers, who experienced the same take-over scenarios without the automated system. No TOR or other warning was presented to the reference drivers. The automated-driving participants were distracted by the visual-manual Surrogate Reference Task (SuRT) (ISO, 11.2012) in order to simulate non-driving-related tasks which are carried out prior to the take-over. The take-over occurred in the right lane, and there was no other traffic present in the setting, enabling an evasive maneuver or lane change. For the evaluation of the experiment, a variety of timing metrics was assessed, among them the *GazeReactionTime*, *EyesOnRoadTime*, *HandsOnTime*, as well as the *Take-OverTime* (cf. Figure 3.1). Regarding the take-over quality, the maneuver type (brake / lane change), as well as *Long.Acc.* and *Lat.Acc.* were considered.

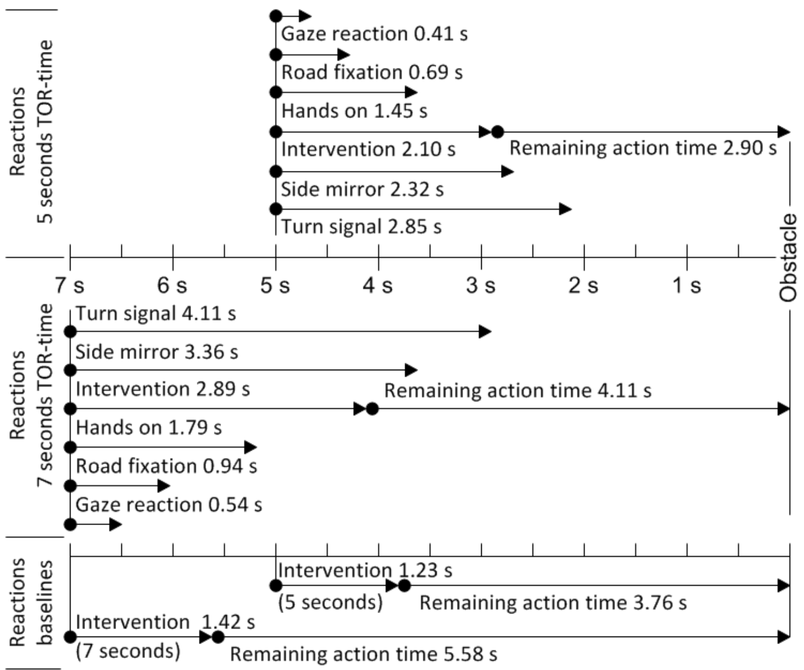



Figure 3.1: Timing aspects of the take-over in Experiment 1 (Gold, Dambock, et al., 2013).

**Results:** The results indicate that timing aspects of the take-over are prolonged for the participants with the 7-seconds TB. Conversely, participants with a TB of 5 seconds showed faster reactions in all timing-related measures, while the magnitude of the timing metrics in the experiment (Figure 3.1) is in line with the values of the study of Zeeb et al. (2015), Kerschbaum et al. (2014), or Lorenz et al. (2014). The quality metrics, however,

[1]The experiment was designed in cooperation with Dr. Lutz Lorenz (BMW AG) and conducted with the assistance of Claudia Pötzinger as part of her diploma thesis (Pötzinger, 2013)

indicate a worse take-over quality with more braking for the participants with a TB of only 5 seconds. According to literature (Damböck et al., 2012; Beukel & Voort, 2013), shorter TBs lead to a reduced take-over performance. When comparing the take-over performance to the manual-driving reference group, manual drivers performed better than automated drivers, although they had no preliminary warning, which is in line with other research (Young & Stanton, 2007a; Shen & Neyens, 2014). They produced less than half of the accelerations and managed the situations almost without any usage of the vehicle's brakes, whereas more than 50% of the participants in the automated condition braked in the take-over situation, which is in line with ratios found by Lorenz et al. (2014).

**Summary:** An increased TB leads to slower but improved driver reactions. The drivers seem to use the additional two seconds for an extended assessment of the situation and a more judicious and calm response. The results further indicate that distracted automated driving with a TB of up to 7 seconds in take-over situations still leads to a worse performance compared to attentive manual driving.

With respect to the modeling of take-over scenarios, the experiment forms the basis of the established data base with two sampling points for modeling the influence of the factor *TimeBudget* on take-over performance.

### 3.3.2 Experiment 2: Automated Brake Application

Providing a sufficient TB in future HAVs will be especially challenging in take-over scenarios, in which the system limit is detected by in-vehicle sensors, as sensor ranges will be limited. The second study[2] therefore focused on extending the TB by an automated brake application simultaneous with the TOR (Gold, Lorenz, & Bengler, 2014). This is also considered to be a promising way of reducing the criticality of take-over situations and showed effectiveness in the context of partially automated driving (Itoh, Horikome, & Inagaki, 2013). By automated brake applications, the kinetic energy of the vehicle is reduced and additional parts of a second are gained for the take-over. This means that the driver has additional time, which showed the potential to improve the take-over quality. It was further hypothesized that braking leads to a more urgent character of the TOR and thus to faster reactions.
In the experiment, a deceleration lasting 1.8 seconds was applied together with the TOR, with a magnitude of $5\,m/s^2$ in one group of participants and $3.5\,m/s^2$ in another. The duration of the deceleration was limited to 1.8 seconds in order to end the automated braking before the participants started their maneuver. By means of this design, the deceleration could not interfere with the response of the drivers. The automated deceleration gained an additional 1.09 and 0.5 seconds, leading to a TB of 6.09 and 5.5 seconds, respectively. As the representation of the accelerations was essential, the experiment was conducted in the dynamic driving simulator. A third group was tested without automated brake application and thus had a TB of 5 seconds. In total, 48 drivers participated in the study, forming three groups of 16 participants each. In a within-subject

[2]The experiment was designed in cooperation with Dr. Lutz Lorenz (BMW AG) and conducted with the assistance of Georg Soyer as part of his master thesis (Soyer, 2013)

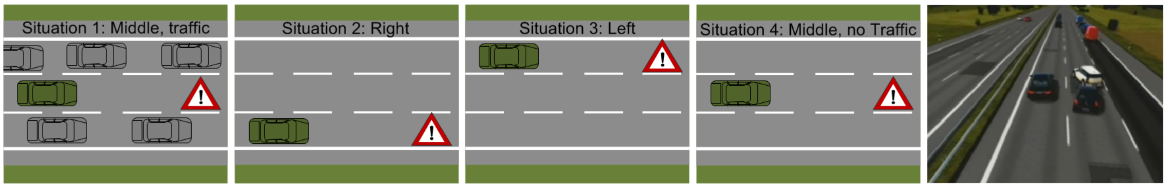



Figure 3.2: Take-over scenarios (Gold et al., 2014).

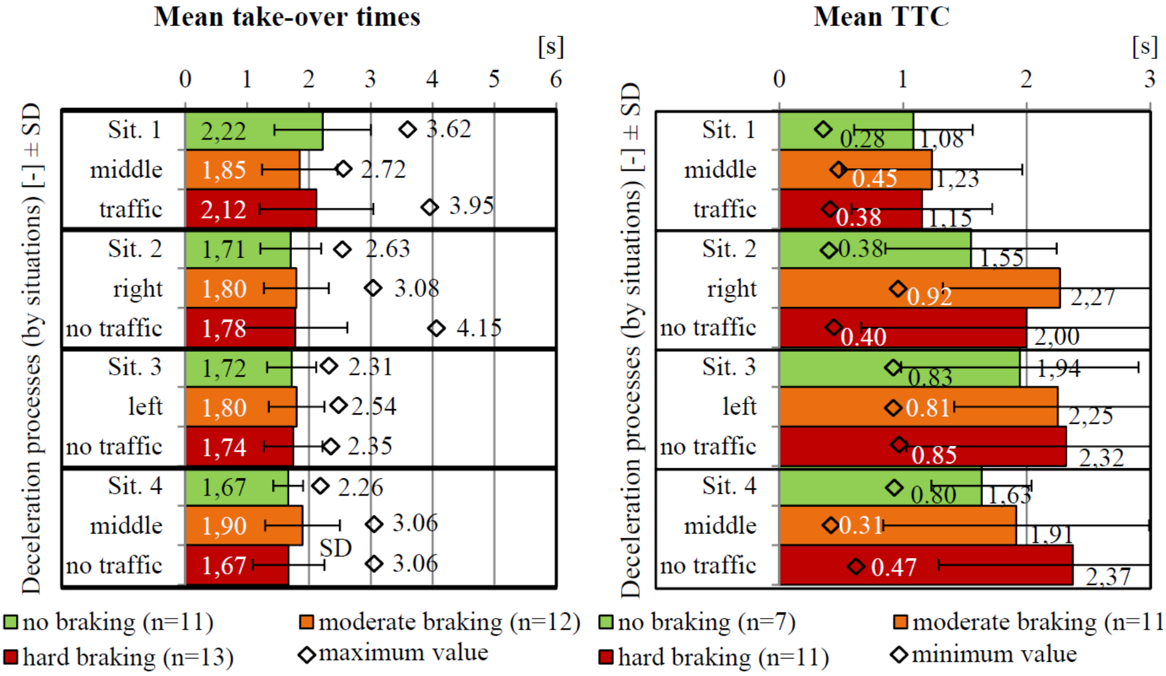



Figure 3.3: Selected results of Experiment 2 (Gold et al., 2014).

design they experienced four take-over situations, while the lane where the take-over occurred was altered. Moreover, one situation included dense traffic in the neighboring lanes, meant to prevent an initial lane change in the situation (cf. Figure 3.2) and increase the complexity of the scenario. In all conditions, participants were engaged in the SuRT. The take-over performance was assessed by the *Take-OverTime*, *Long.Acc.*, *Lat.Acc.*, *TTC*, and *Crash*.

**Results:** Surprisingly, the automated brake application did not shorten temporal aspects of the take-over (cf. Figure 3.3), and more than two thirds of the participants did not notice the automated brake applications, an effect also found in real vehicle experiments (Hoffmann, 2008). Overall, automated braking did not have a strong influence on take-over performance. Lateral accelerations appeared to be lower ($p = .079$), which is likely caused by a combination of the extended TB and a lower vehicle speed due to automated braking. There is also an indication that automated braking reduces crash probability ($p = .064$) in the high-traffic condition. The high complexity, represented by a high traffic density of 30 vehicles/km, had a strong influence on take-over performance, inducing higher crash probabilities, higher longitudinal accelerations and shorter minimal TTCs (cf. Figure 3.3). This effect was dominant in the results and significant in most of the dependent variables.

**Summary:** While the automated brake application was shown to potentially improve take-over performance without impairing the driver in the take-over scenarios, the complexity due to dense traffic significantly reduces take-over performance and leads to an increased crash risk.

The experiment introduces the factors *TrafficDensity*, *Lane* and *AutoBrake* into the model data base, enabling the consideration of these factors in the following modeling approach.

### 3.3.3 Experiment 3: Cognitive and Visual Tasks

The third study[3] compared the visual-manual SuRT with the cognitive 2-Back task (Reimer, Mehler, Wang, & Coughlin, 2010) in an experiment in the dynamic driving simulator (Radlmayr, Gold, Lorenz, Farid, & Bengler, 2014). With the cognitive task, participants were able to keep their eyes on road and thus had the possibility to remain partially in the control loop by monitoring the system and the situation. It was hypothesized that drivers with their eyes on the road and a solely cognitive distraction show higher take-over performance, compared to the visually engaged group.
Apart from the absence of automated brake applications, the scenarios were similar to those implemented for Experiment 2 (Subsection 3.3.2, Figure 3.2). Participants had a TB of 7 seconds, and the system limit was represented by the accident blocking the current lane. The experiment also contained the high traffic scenario.
Forty-eight drivers participated in this study and were subdivided into three groups of 16 participants each. Apart from the groups engaged with the SuRT and 2-Back task, a third group drove without the automated system but was also engaged in the cognitive 2-Back task. This group served as a reference condition. Unlike the manually driving group in Experiment 1, the auditory warning was also provided to the the reference group. Driver's performance was assessed by the *Take-OverTime*, *Long.Acc.*, *TTC*, and *Crash* risk.

**Results:** In line with Experiment 1, participants driving manually started their maneuver sooner than drivers in the automated conditions (cf. Figure 3.4), an automation effect that has already been described (Young & Stanton, 2007a; Shen & Neyens, 2014). There were only small differences in the performance between the SuRT and the 2-Back group. The *Load* was only found to influence *Crash* (more crashes in the SuRT condition, Figure 3.4), whereas it did not have an effect on *Take-OverTime* nor on the quality metrics *Long.Acc.* and *TTC*. Regarding *TrafficDensity*, results of this study were in line with Experiment 2, as participants generated higher decelerations, more crashes and lower minimum TTC-values when there was traffic present.

**Summary:** "Cognitive non-driving[-related] tasks can lead to a similar distraction and thus loss of situation awareness compared with mainly visual tasks" (Radlmayr et al., 2014, p. 5). Furthermore, the complexity of the scenario, represented by high traffic

[3]The experiment was designed in cooperation with Dr. Lutz Lorenz (BMW AG) and conducted with the assistance of Jonas Radlmayr as part of his diploma thesis (Radlmayr, 2013)

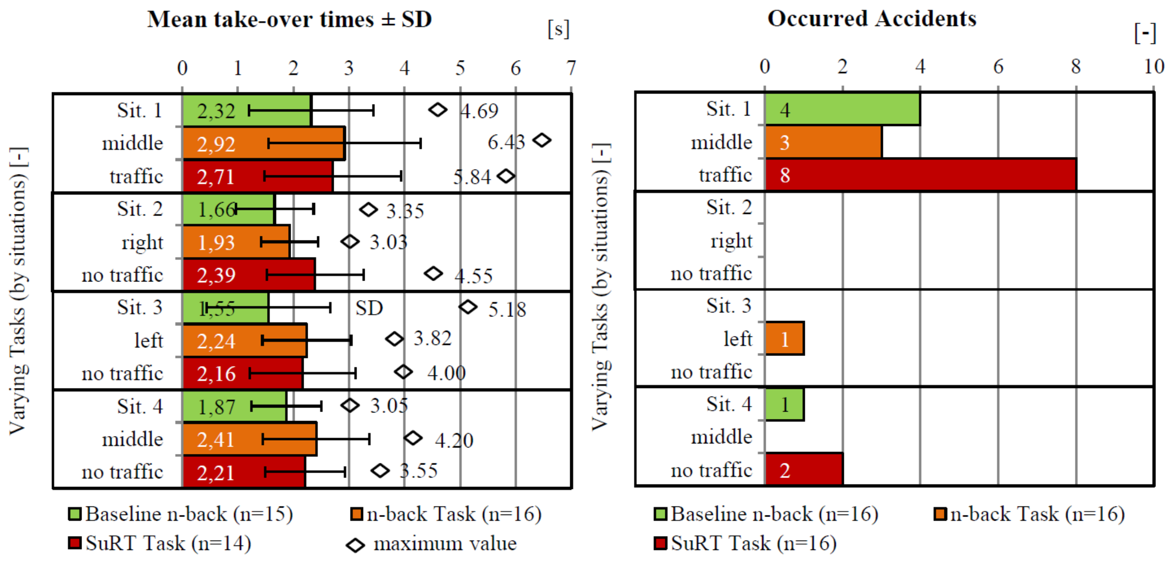



Figure 3.4: Selected results of Experiment 3 (Radlmayr et al., 2014).

densities, proved to be an important factor that plainly impairs the drivers' take-over performance.

Regarding the subsequent modeling approach, the experiment expands the data by a standardized cognitive task in different traffic conditions and additional take-overs in various lanes (factors *Load* & *Lane*).

### 3.3.4 Experiment 4: Traffic Density

Experiment 2 and 3 showed distinct differences in take-over performance when comparing scenarios without traffic to a scenario with a very high traffic density in the neighboring lanes. The chosen number of vehicles per kilometer was approximately 30 vehicles/km. Under normal traffic conditions, such densities are not stable and therefore likely to occur in traffic jams or at lower vehicle speeds only (cf. Schöpplein, 2013; Kühne et al., 2004). As the complexity of the scenario and thus the surrounding traffic proved to be an important influencing factor and as only the anchor points 0 and 30 vehicles/km had been considered in the previous experiments, Experiment 4[4] assessed the influence of medium traffic densities on take-over performance (Gold et al., 2016).
Seventy-two participants took part in this study in the fix-based driving simulator. Apart from a no-traffic condition, medium traffic conditions with 10 and 20 vehicles per kilometer were implemented and varied among subjects. The lane in which the take-over took place was also changed for the individual subjects.
As cognitive distraction was identified as a relevant influencing factor in Experiment 3, the 20-Questions task was introduced, which is used in experimental conditions as a substitution for cell-phone conversations (Merat et al., 2012). Neubauer et al. (2012) identified faster brake reactions when participants were involved in a phone call,

[4]The experiment was conducted with the assistance of Shiquiang Xie and David Lechner as part of their master/bachelor thesis (Xie, 2014; Lechner, 2015)

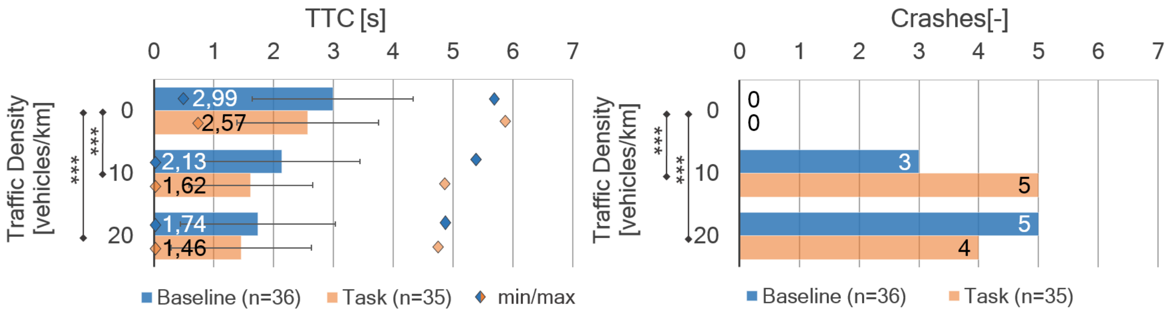



Figure 3.5: Selected results of Experiment 4 (Gold et al., 2016).

compared to a group of drivers with no additional task. To reproduce this interesting finding, half of the participants in Experiment 4 performed the verbal 20-Questions task, while the other half did not have to complete any non-driving-related task. In both conditions, participants were able to keep their eyes on the road. The take-over performance was assessed by the variables *Take-OverTime*, *HandsOnTime*, *Long.Acc.*, *Lat.Acc.*, *TTC*, and *Crash*.

**Results** confirmed the impairment of the take-over performance due to the presence of surrounding traffic. In the two conditions involving traffic, the take-over time was prolonged, measured accelerations and crash risks were higher and the TTCs were lower. These effects arose between the no-traffic condition and the conditions involving traffic, while there were no significant effects between conditions with 10 and 20 vehicles/km. In general, effects due to the task conditions were minor. The non-driving-related task only showed a significant effect for the TTC-values, with lower, more critical TTCs in the 20-Questions task condition. The results therefore could not confirm the findings of Neubauer et al. (2012).

**Summary:** The 20-Questions task, a substitution for a cell-phone conversation, showed minor effects on take-over performance, compared to the no-task condition. An increased complexity of the scenario, however, showed an impaired take-over performance in the vast majority of measures. The pure presence of traffic causes the decrease in performance, rather than the amount of traffic.

In connection with modeling the take-over, the experiment adds another non-driving-related task to the factor *Load* and two additional sampling points, crucial for modeling the influence of the factor *TrafficDensity* and thus a scenario's complexity.

### 3.3.5 Experiment 5: Non-Driving-Related Tasks

As shown above, different non-driving-related tasks have already been examined. Even with studies with a design very similar to this thesis, it is difficult to compare performance in dependence of the task across experiments, as the conditions, methods, and independent factors vary among the authors. Petermann-Stock et al. (2013), for example, compared an auditory, auditory-visual, and an auditory-visual-motoric non-driving-related task in take-over scenarios of HAVs. However, the take-over scenarios were implemented in a rather uncritical way and, unlike the scenarios reported on in this thesis,

Table 3.2: Qualitative assignment of tasks (Gold, Berisha, & Bengler, 2015).

| | Visual | Motoric | Cognitive |
|---|---|---|---|
| SURT | X | X | |
| Text | X | X | X |
| MT | | X | X |
| 2-Back | | | X |

did not demand an immediate take-over, strong braking, or an evasive maneuver. The *Take-OverTime*, for instance, showed effects of the non-driving-related tasks, but because of a reduced urgency, times are comparatively long.
Therefore, the fifth experiment[5] focused on comparing non-driving-related tasks of different types (Gold, Berisha, & Bengler, 2015), involving different modalities (cf. Table 3.2) and a similar design as in the previous experiments. Apart from a mainly manual task (MT) and a naturalistic fill-in-the-blank text task (Text), the SuRT and 2-Back task were considered in order to prove comparability of the prior experiments. The study was conducted in the fix-base driving simulator with 24 drivers. During a familiarization drive, participants experienced twelve take-over scenarios in manual mode, represented by a broken down vehicle in the current lane. The last three of the twelve training situations were used as a baseline condition. In the subsequent experimental condition, the four tasks were varied in a within-subject design. Participants had to engage in the tasks, while twelve take-overs occurred unpredictably. Similar to the baseline condition, drivers had a time budget of 7.8 seconds, and there was no other traffic in the neighboring lanes. The *Take-OverTime*, *Lat.Acc.*, *Long.Acc.*, and *TTC* were selected as measures of take-over performance.

**Results:** Results regarding the influence of the non-driving-related task were divergent. The manually driven baseline and the 2-Back task showed the fastest *Take-OverTime*; the manual task had the longest *Take-OverTime*, but at the same time the lowest *Lat.Acc.* The 2-Back task resulted in higher *TTC* values compared to all other conditions. In a subjective rating, the fill-in-the-blank text task was assessed to be the most impairing task with regard to the stressfulness of the take-over scenario, although this task did not induce a worse take-over performance. In the third experiment (Radlmayr et al., 2014), no significant differences between the SuRT and 2-Back task were found. In this experiment, the SuRT led to a longer *Take-OverTime* and a lower *TTC*, indicating a lower take-over performance compared to the cognitive 2-Back task. Altogether, the non-driving-related tasks showed smaller effects than initially hypothesized (cf. Figure 3.6).

**Summary:** While several effects of the tested non-driving-related tasks were found, the magnitude of these effects was rather small. The 2-Back task appeared to be the most prominent as it induced a higher take-over performance compared to the other tasks.

For modeling driver's performance in take-over scenarios, the experiment spanned a wide range of non-driving-related tasks (*Load*), allowing a profound mapping of different non-driving-related tasks in the subsequent modeling.

[5] The experiment was conducted with the assistance of Ilirjan Berisha as part of his bachelor thesis (Berisha, 2013)

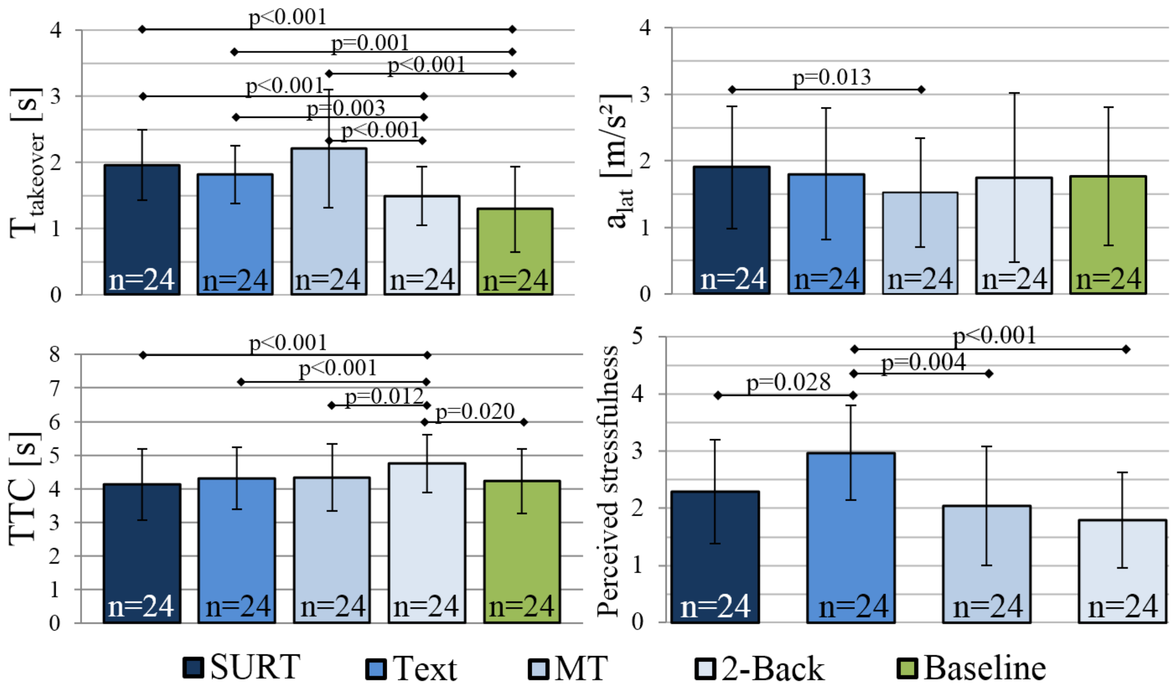



Figure 3.6: Selected results of Experiment 5 (Gold, Berisha, & Bengler, 2015).

### 3.3.6 Experiment 6: Age and Trust in Automation

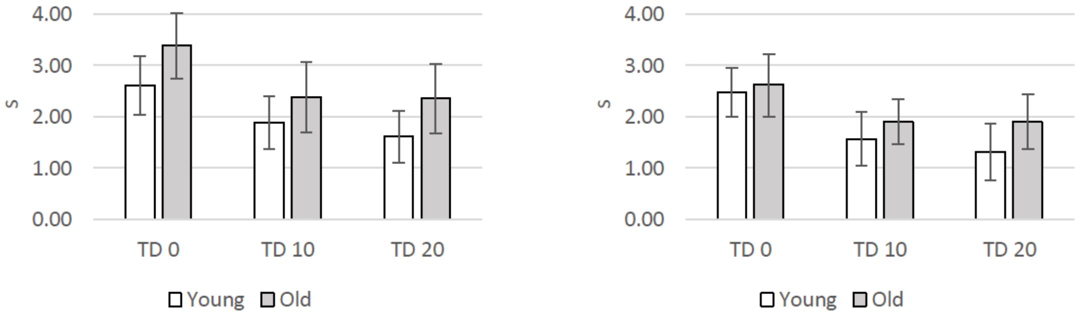
Another factor that has been identified is the driver with his varying abilities and skills, leading to variance among the dependent variables. This means that reaction times (Kováč, 1969; Welford et al., 1980) and the ability to process information (Körber & Bengler, 2014) can vary in dependence of a person's age and can lead to an impaired take-over performance of elderly drivers. The participants of Experiment 4 were therefore selected depending on their age, forming two age groups, one with drivers younger than 28 years, the other one with drivers older than 60 years. Technically, Experiment 6 is not a separate experiment, but the evaluation of Experiment 4 regarding the factor *Age*, presented also in a separate article (Körber, Gold, Lechner, & Bengler, 2016). For measuring the influence of driver's age, the variables *Take-OverTime*, *Lat.Acc.*, *Long.Acc.*, and *TTC* were considered.

**Results:** In line with results of Petermann-Stock et al. (2013), the factor of driver's age did not reveal an effect on the *Take-OverTime*, although the scenarios were designed in a significantly more complex and time-critical way. In contrast to simple reaction time research, the *Take-OverTime* seems to be less sensitive to the age of the participants, either because of a less controlled experimental condition, or due to (over-)compensatory strategies of elderly drivers. Although the *Take-OverTime* did not differ among the groups, elderly braked more intensively and generated higher minimum TTC values compared to the younger drivers (cf. Figure 3.7). This also indicates that driving strategies differ among the groups. In addition, elderly drivers caused fewer accidents, although this lacks statistical significance.

*Results of an ANOVA on minimum TTC.*

| | *F* | *df* | *Partial* $\eta^2$ | *p* |
|---|---|---|---|---|
| Age | 5.19* | 1, 50 | .09 | .027 |
| Task | 5.53* | 1, 50 | .10 | .023 |
| Traffic Density | 18.48*** | 2, 100 | .27 | .001 |
| Age*Task | 0.00 | 1, 50 | .00 | .981 |
| Age*Traffic Density | 0.23 | 2, 100 | .01 | .793 |
| Task*Traffic Density | 0.05 | 2, 100 | .00 | .954 |
| Age*Task*Traffic Density | 0.75 | 2, 100 | .02 | .475 |

*Note.* * $p < .05$; *** $p < .001$.




*Minimum TTC of participants without additional task; error bars = 95% confidence interval.*

*Minimum TTC of participants with additional task; error bars = 95% confidence interval.*

Figure 3.7: Selected results of Experiment 6 (Körber et al., 2016).

**Summary:** While the *Take-OverTime* of the age groups did not differ, elderly drivers showed a differing driving strategy, involving intensified braking, which lead to a reduced criticality of the take-over situations.

In terms of modeling the driver in take-over scenarios, the experiment completes the selected factors by introducing a relevant number of elderly participants to the data-set and thus enabling a consideration of the factor *Age* in the subsequent modeling.

## 3.4 Model Selection

In Section 2.7, different ways of modeling the driver in take-over scenarios were proposed. Based on the experimental results, the suitability of these approaches is discussed below and a model is selected, promising an adequate quantitative model of take-over performance which makes it possible to draw conclusions about the influencing factors and enables a deeper understanding of human-automation interaction in take-over scenarios of HAVs.

### 3.4.1 Common Driver Models in Near-Crash Situations

The models reviewed for near-crash situations (Subsection 2.7.1) are based on manual-driving data and do not model automation effects that can arise in take-over experiments. While the perception of driving-relevant signals is continuous in manual driving, drivers in HAVs do not have to and are unlikely to monitor the system and the driving-related situational parameters. Compared to manual drivers in near-crash situations, automated driving participants in take-over scenarios first have to regain awareness of the situation, the state of the automation, the system limit, and the different possible responses to the TOR. The time drivers need for this process of re-engagement could be modeled by an increased delay of the drivers' responses within the existing models in near-crash situations. Nevertheless, experiments show an impaired driving performance right after the take-over. In addition, different explanatory variables such as the strain on the driver or the time budget exist and cannot be considered in the current models of near-crash situations. Even for very similar manual-driving scenarios, "it seems likely that the high complexity of driver behavior will continue to force researchers to limit their modeling scope so as to fit the specific application at hand, just as it has for the authors of the reviewed articles" (Markkula et al., 2012, p. 1135). Take-over scenarios deviate even more from the reviewed models, which is why different model approaches should be pursued when modeling take-over performance.

The models describe driver's response in the time domain, which appears to be hardly feasible for automated driving at the current point in time, due to limited knowledge of the human-automation interaction in HAVs, but also because the task of taking over vehicle control is not as continuous as manual driving. Given the resulting variability of driver responses, the model should be simplified to response metrics as a function of the different influencing parameters, rather than modeling take-over behavior in the time domain.

### 3.4.2 Modular Additive System

The modular additive system approach in Subsection 2.7.2 has several characteristics that are valuable for modeling take-over performance in automated vehicles. This approach enables the validation and supplementation of the model by other authors, and the operationalization is straightforward. The elements can be combined independently, which is why the approach covers a wide variety of different take-over scenarios and combinations of factors. By simply adding elements, a future diversification of the modular additive system is possible. Additionally, segments can be derived from existing research, such as the simple reaction times, and be based on established models, such as the Model Human Processor.

On the other hand, the approach is based on the assumption that the dependent variables can be described by a linear combination of the explanatory variables. The take-over process, however, is a sequential process, at least in parts. The visual and motoric reorientation, for example, are likely to be performed in parallel (cf. Figure 2.10 and Zeeb et al., 2015). Simplification to a sequential process, as in the additive model, might impair the prediction accuracy to an uncertain extend. Additionally, as seen in the experiments, the segments are not independent from each other. Drivers compensate shorter TBs, for instance, by accelerating the take-over by a shortening of different segments. The worsening of the take-over quality in more time-critical scenarios further indicates that responses are selected and executed by the driver before the cognitive take-over can be considered to be complete (cf. Figure 2.10), which could have been predicted, "since in most tasks the cognitive processes run partly parallel (particularly under time pressure

conditions)" (F. Chen, 2006, p. 78). This proves the existence and relevance of parallel processes in the take-over behavior, and in these cases, a linear combination of the segments no longer provides a valid prediction of take-over times.
Another drawback of this modeling approach is the limitation with regard to quantifying and predicting take-over quality. It can only be roughly estimated by looking at the TB in comparison to the predicted take-over and maneuver time. As necessary assumptions for the model approach are violated and the ability of the model to limit take-over quality is restricted, the modular additive system is not considered further.

### 3.4.3 Artificial Neural Networks

In most cases, ANNs have the ability to model a wide variety of behavior with an excellent model fit. The examiner does not have to make presuppositions which is why effects in the data are modeled that could not be revealed with the help of other descriptive methods.
In a pre-test, the data-set was fed to an ANN with two hidden layers. Seventy percent of the data was used for training the network (algorithm: Levenberg-Marquardt), 15% for validation purposes, and the remaining 15% for testing the model. Figure 3.8 does not indicate any problems when training the data, as results of validation and test converge and only slightly differ from the training.

When looking at the model fit (Figure 3.9), the R-values indicate that the major part of the variance within the data can be explained by the model. By feeding the model with new data, the take-over performance can be predicted. For a TB of 5 seconds, a traffic density of 0 vehicles/km, the SuRT task as a non-driving-related task, and a driver's age of 26 years, the model predicts a *GazeReactionTime* of 0.46 seconds for the first take-over, which is reasonable, when compared to, for example, Figure 3.1 of Experiment 1, where drivers of a similar age showed a mean *GazeReactionTime* of 0.41 seconds under equivalent conditions.

While the ANN proved to be a suitable method for modeling driver's take-over performance, it is a rather untransparent way of modeling the system, replacing one black box

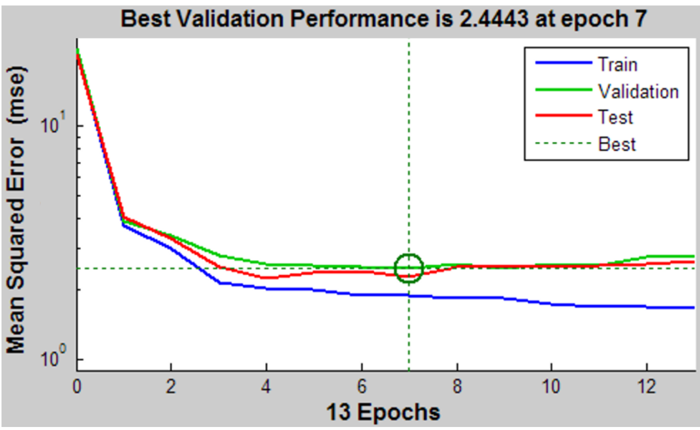



Figure 3.8: Performance of training, validation, and test of the ANN.

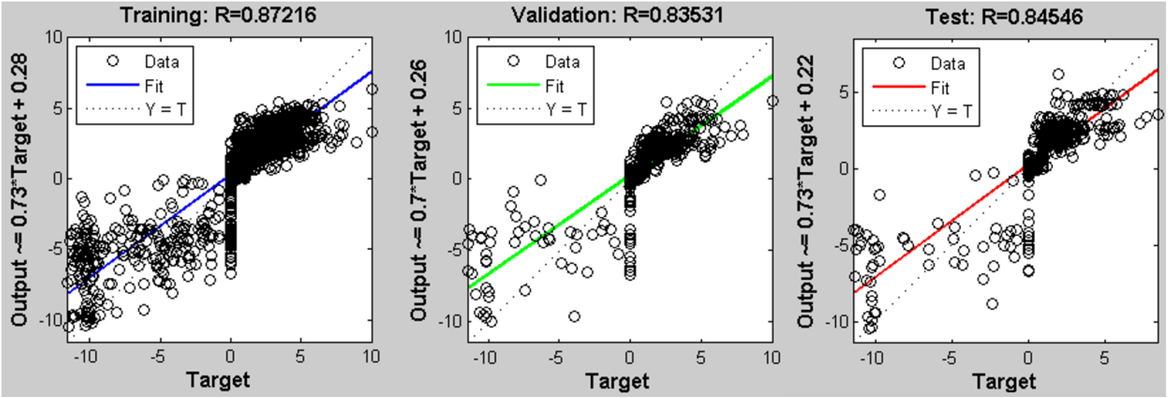



Figure 3.9: Model fit for training, validation, and test data of the ANN.

by another. The resulting model cannot be described by linear algebra and dependencies of input and output variables are not exposed, which is why conclusions about the adverse effect of factors on take-over performance can only be approximated. As the model should support and enable an understanding of the take-over process, human performance and the influencing factors on safety, ANNs are avoided for the subsequent modeling.

### 3.4.4 Regression Analysis

Compared to ANNs, regression analysis requires a basic understanding and previous examination of the system subject to the modeling in order to be able to set up valid regression equations. In return, regression analysis provides a representation of the system by a set of linear or non-linear equations that also yield a plain description of the adverse effect of explanatory variables on the output. As a disadvantage, the model fit is dependent on the regression equations and likely to show an inferior fit compared to ANNs. Nevertheless, this leads to a minor probability of over-fitting the test data and thus to a higher potential of predicting the actual take-over performance. As the goal is not only to create a quantitative model of take-over performance, but also to explain the governing factors, regression analysis was chosen for the modeling approach in this thesis. It has the ability to model a variety of correlations, only limited by the effort invested to set up the regression equations. It further serves as a model disclosing the coherence between the variables, and the modeling can be extended by introducing advanced regression methods such as mixed-effects regression analysis or regressions allowing for consideration of different distributions of test data. Hereafter, regression analysis is used for modeling take-over performance in different time-critical take-over scenarios.

# 4 Modeling Take-Over Performance Using Regression Analysis

In the following chapter, a modeling approach using regression methods is proposed, first describing principles of regression models, the data, input and output parameters, derived assumptions, the regression equations and discussing the models and their fit.

## 4.1 Algorithms for Parameter Determination and Regression Implications

The most common type of regression is the linear regression (Equation 4.1). The *response* $y$ is modeled by a linear combination of a set of predictors $x$ and regression parameters $\beta$. The regression is considered linear in $\beta$, while the predictors do not necessarily have to be of linear type (Montgomery & Peck, 1992). As soon as at least one $\beta$ shows non-linearity, the regression is considered non-linear (Equation 4.2). Many non-linear systems can be transformed to linear ones by the use of data-transformation, such as logarithmic functions or changes in the regression equation (Equation 4.3). As a drawback, this may complicate the interpretation of the equations and the regressions' results and induce problems of collinearity (cf. Subsection 4.1.2), which is why transformation is avoided in some regressions of this thesis. There are several other regression methods used in this thesis, namely robust regression (Subsection 4.5.1.2) and generalized linear models (Subsection 4.5.2.2) for handling outliers and non-normally distributed errors, mixed-effect models (Subsection 4.5.3) for modeling random variance and logistic regressions (Subsection 4.4.7 & Subsection 4.5.2.1) for nominal response variables.

$$Linear\ Regression : y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + ... + \beta_n x_n + \epsilon \tag{4.1}$$

$$Non-Linear\ Regression : y = \beta_0 + \beta_1 * (\beta_2 + x_2)^2 + \epsilon \tag{4.2}$$

$$Linear\ Regression,\ equal\ to\ 4.2 : y = \beta_0 + \beta_1 x_1 + \beta_2 x_1^2 + \epsilon \tag{4.3}$$

### 4.1.1 Least Squares Estimation

In a regression, $\beta_x$ is estimated so that the output resembles the measured data. This is done by estimating $\beta$ such that the sum of the squared distances between the measured data and the output data is minimized, which is by far the most commonly used method (Cohen, 2003) and is referred to as Ordinary Least Squares (OLS). OLS is assumed to be the best linear unbiased estimator; however, violations of assumptions, such as outliers, may be too influential (Cohen, 2003). Testing and detection of violations is therefore important when conducting OLS-regressions, to ensure adequacy of the model.

$$f(OLS) = min(\sum (Y_i - \overline{Y}_i)^2) \tag{4.4}$$

### 4.1.2 Impaired Model Adequacy

Fitted models have to be checked for model adequacy and validity. While model adequacy can be assessed based on the evaluation of parameters and meaningfulness of the resulting equation, new data is needed for the validation of the model. There are several issues possibly leading to a lack of model adequacy and different ways to detect and face them.

#### Under- and Overfitting

Figure 4.1 shows examples of underfitted and overfitted models. On the left side, an exponential correlation (dashed line) of the training data is represented by a linear model (straight, solid line). Besides a possibly high error, extrapolation would lead to poor predictive characteristics of the model. An overfit is characterized by a model which is tailored for the current data-set (e.g. by high exponential terms or too many predictors), but not valid for new data or extrapolation. On the right side of Figure 4.1, the model matches all data points by the use of a high exponential term (solid line). The degree of the term matches the degree of freedom of the model, whereas the real correlation seems to be rather linear (straight, dashed line). When considering new data or extrapolating, high deviations become evident, proving that the model is not valid. The regression equation should therefore be confirmed by theoretical models, physics and knowledge from literature in order to avoid over- and underfitting and thus impaired validity.

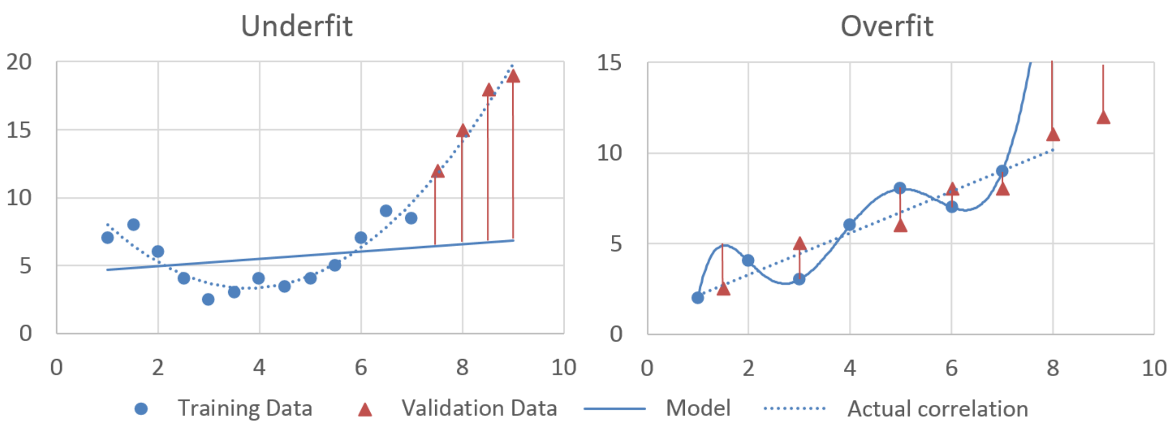



Figure 4.1: Examples for under- and overfitting of regression models.

#### Non-normally Distributed Errors

For different reasons, every data-set raised by measuring the response of a system is subject to variance in the system and the measuring instrument. For parameter estimation and interference statistics, estimators assume the variance in the resulting data to be normally distributed. As a consequence, the error of the model is considered to follow a normal distribution as well. If this assumption is violated, for example due to a skew distribution of measures, model adequacy is impaired. Although regressions are rather robust regarding the distribution of input data, "gross non-normality is potentially more serious as the t- of F-statistics, and confidence and prediction intervals depend on the normality assumption" (Montgomery & Peck, 1992, p. 136).

#### Multi-collinearity and Variance Inflation Factor (VIF)

Some predictors may correlate, either accidentally or causally. The quantity of sunshine hours in a day is, for example, likely to correlate with the maximum temperature. If both sunshine hours and temperature are used as predictors within the same model, contribution of the different predictors cannot be reliably estimated, and variance in the estimators increases. The result may fit the data, but interpretation is possibly misleading. Belsley, Kuh, and Welsch (1980) defined that two variables are collinear if one of the vectors (representing the variable) is a linear combination of the others. Some sources of collinearity can be avoided by selecting a suitable method for data collection and appropriate predictors. Collinearity is revealed by high correlations within the predictors. Furthermore, the Variance Inflation Factor (VIF) was introduced. "The VIF for each term in the model measures the combined effect of the dependencies among the regressors [predictors] on the variance of that term" (Montgomery & Peck, 1992, p. 296). Large VIFs indicate that the term is affected by collinearity.

### 4.1.3 Checking Model Adequacy

The quality of the models and their predictions can be evaluated by means of various methods. It makes sense to examine the difference between the prediction of the model and the measured values. This difference is called residual (Equation 4.5), and smaller residuals suggest a better model fit (an exception is a possible model *overfit*). Residuals should be normally distributed, meaning that the majority of the residuals' modulus should be small, and positive and negative residuals should appear equally. If the distribution of the residuals is skewed, predictions tend to estimate either too high or too low values. Furthermore, the variance of the residuals should be independent from the predictions. If residuals show a higher variance for certain ranges of prediction, the model's prediction in this range is less accurate. Another very common method for evaluating model fit is the consideration of the r-squared ($R^2$; Equation 4.9) or coefficient of determination, as an indication for the percentage of variance in the data that can be explained by the model. $R^2$ approaches 1 for a high proportion of explainable variance and 0 for no variance in the data that is explained by the model. Furthermore, $R^2$ rises with the number of

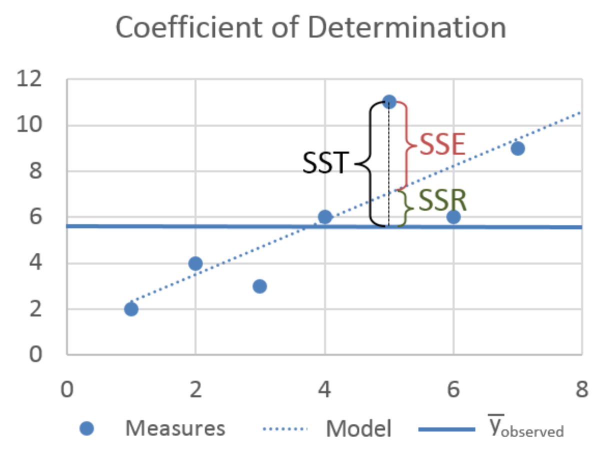



Figure 4.2: Visualization of SSE, SSR & SST.

dependent variables as the degrees of freedom decrease. In order to correct for this error, the adjusted $R^2$ (denoted as $\overline{R}^2$) is reported in this thesis as shown in Equation 4.10.

$$r_i = y_{i-observed} - y_{i-predicted} \tag{4.5}$$

$$SSE = \sum_{i=1}^{n} (y_{i-observed} - y_{i-predicted})^2 = \sum_{i=1}^{n} r_i^2 \tag{4.6}$$

$$SSR = \sum_{i=1}^{n} (y_{i-predicted} - \overline{y}_{observed})^2 \tag{4.7}$$

$$SST = SSE + SSR = \sum_{i=1}^{n} (y_{i-observed} - \overline{y}_{observed})^2 \tag{4.8}$$

$$R^2 = \frac{SSR}{SST} = 1 - \frac{SSE}{SST} \tag{4.9}$$

$$\overline{R}^2 = 1 - \frac{n-1}{n-p} * \frac{SSE}{SST} \tag{4.10}$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} r_i^2} \tag{4.11}$$

The achievable $R^2$ is dependent on the variance present in the data. To model human behavior, according to the measure, a low $R^2$ can still indicate a good model, as a large degree of variance that cannot be explained by objective factors may be induced by the human. It has to be further mentioned that, although a high $R^2$ suggests a strong correlation of the model and the dependent variables, there does not necessarily have to be a causal relationship. In order to argue for a causal relationship, the regression has to be supplemented with knowledge gained otherwise. The Root-Mean-Square Error (RMSE) correlates with the residuals, as it is the root of the mean of squared residuals

(Equation 4.11) and another common measure for assessing model fit. It also makes it possible to estimate the mean deviation of predicted and observed values.

As already mentioned, modeling with regression methods is an iterative process. Originating from a regression equation that is based on explanatory data assessments and theoretical models, the resulting regression is used to further improve the equation. In order to do so, the contribution of each of the explanatory variables has to be evaluated. On the one hand, regression analysis provides p-values for each of the predictors for the null hypothesis that the predictor does not influence the model. Considering a significance level of $\alpha{=}.05$, a $p{<}.05$ of a coefficient indicates that this coefficient is likely to have an effect on the model (significant influence). As regression also offers t-statistics of the coefficients, the size of the effect has been estimated by calculating effect sizes like Pearson $r$ (Equation 4.12; $r{>}.10 \rightarrow small, r{>}.30 \rightarrow medium, r{>}.50 \rightarrow large$ (Cohen, 1992)) or the Cohen's $d$ (Equation 4.13; $d{>}.20 \rightarrow small, d{>}.50 \rightarrow medium, d{>}.80 \rightarrow large$ (Cohen, 1988)).

$$r = \sqrt{\frac{t^2}{t^2 + df}} \tag{4.12}$$

$$d = \frac{2t}{\sqrt{df}} \tag{4.13}$$

The charts in Figure 4.3 allow for a further assessment of the residuals and therefore the model.

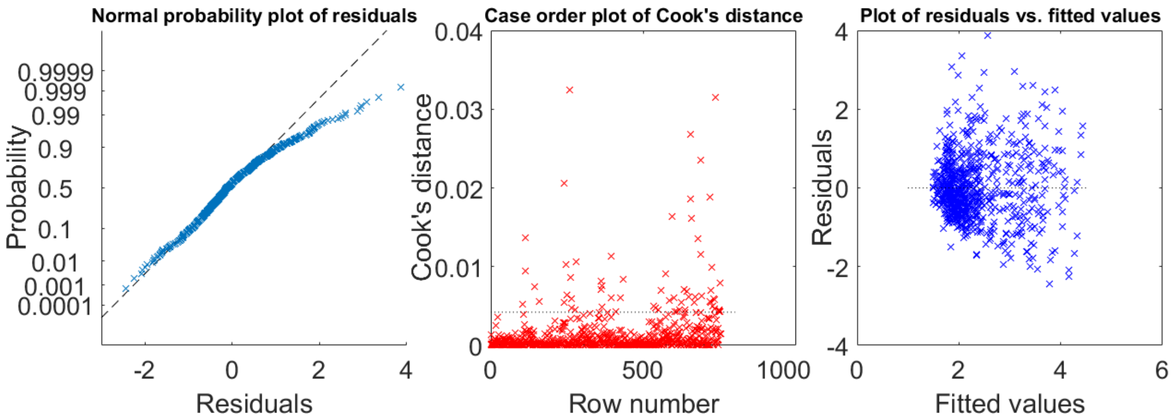



Figure 4.3: Examples of Normal Probability Plot (left), Cook's Distance (center) and residuals over fitted values (right).

By using the *Normal Probability Plot of Residuals* (Figure 4.3, left), it is possible to evaluate whether it is reasonable to assume that the residuals are normally distributed. In the *Normal Probability Plot*, the percentiles of a normal distribution (line) and the percentiles of the measures (dots) are plotted. Deviation of the measures (dots) from the line indicate a skewness of the distribution. A disproportional amount of outliers would appear on the left or right of the plot and deviate from the line. In non-normally distributed data-sets of OLS regressions, outliers have an unproportionally large influence on the model.

The centered chart depicts *Cook's Distance* (Cook, 1977) of the data points (Figure 4.3, middle), helping to identify outliers in the data and their impact on the model. These "influential data points, of course, are not necessarily bad data points; they may contain some of the most interesting sample information" (Belsley et al., 1980, p. 3). Equation 4.14 shows the equation for calculating *Cook's Distance*, while $y_{i-predicted(j)}$ is the fitted response of data point $i$ without observation of $j$. In this way, the influence of $j$ is estimated and depicted in the chart. Data points with a high *Cook's Distance* as the point in the upper left have a disproportional influence on the model and should be checked for observational errors or errors made when recording the data. Legitimately occurring extreme observations often contain valuable information that improves the estimation (Belsley et al., 1980) and are kept for the modeling.

$$D_j = \frac{\sum_{i=1}^{n}(y_{i-predicted} - y_{i-predicted(j)})^2}{k * MSE} \tag{4.14}$$

The chart on the right plots the residuals versus the fitted values (Figure 4.3, right). If the distribution of residuals changes over the fitted values, the model's fit is dependent on the range of the response. In the example, residuals on the left are smaller compared to those on the right side. This indicates that the model has a better fit for low output values and worsens with increasing predicted output ("heteroscedasticity").

## 4.2 Data Pool and Processing

The data used for the modeling approach was recorded during the six experiments summarized in Chapter 3 and extracted from the driving simulation and eye-tracking data. The resulting data-set consists of a database with every line / entry representing one take-over. Attributes of the take-overs are the different input and output parameters (Table 4.1 & Table 4.1).

Table 4.1: Input parameters in the data-set.

| Name | Type | Range | Unit |
|---|---|---|---|
| *TimeBudget* | Input | 5;7;7.78 | $[s]$ |
| *AutoBrake* | Input | 0;3.5;5 | $[m/s^2]$ |
| *Lane* | Input | 1-3 | $[-]$ |
| *TrafficDensity* | Input | 0;10;20;30 | $[vehicles/km]$ |
| *Repetition* | Input | 2-20 | $[-]$ |
| *Load* | Input | 0-5 | $[-]$ |
| *EyesOffRoad* | Input | 0/1 | $[binary]$ |
| *Age* | Input | 19-79 | $[years]$ |

Table 4.2: Output parameters in the data-set.

| Name | Symbol | Type | Range | Unit |
|---|---|---|---|---|
| *GazeReactionTime* | $t_{GR}$ | Output | >0 | $[s]$ |
| *Take-OverTime* | $t_T$ | Output | >0 | $[s]$ |
| *Lat.Acc.* | $a_{lat}$ | Output | >0 | $[m/s^2]$ |
| *Long.Acc.* | $a_{long}$ | Output | <=0 | $[m/s^2]$ |
| *TTC* | TTC | Output | >=0 | $[s]$ |
| *Brake* | $P_{(Brake)}$ | Output | 0/1 | $[binary]$ |
| *Crash* | $P_{(Crash)}$ | Output | 0/1 | $[binary]$ |

For the purpose of performing regression analysis, the data was further processed, missing cells were replaced and irregular trials were excluded. Beginning with all recorded take-overs, the following adaptions were made.

**Data Inconsistency and Adjustments of Input Variables:**

- If the non-driving-related task included a visual distraction and was classified as such, take-over situations in which participants were not completely visually distracted and showed glances to the scenery right before the take-over were excluded from the data-set. This was the case in 18 take-overs. It was thus made sure that participants with visually distracting non-driving-related tasks actually were visually distracted when the TOR was prompted.
- In one case, a participant did not recognize the TOR. This was rather unexpected, as the TOR was designed according to NHTSA guidelines (Campbell et al., 2007) and plainly audible with a volume of 75 dB. This take-over was excluded from the data-set and the issue is further discussed in the paper of Gold et al. (2016).
- In 192 take-over situations, originating from Experiment 5 (Subsection 3.3.5), the vehicle model induced rounding errors, leading to a wrong representation of vehicle's speed. While the speedometer indicated a vehicle speed of 120 km/h, actual speed was only 107 km/h. This led to a prolonged TB of 7.78 seconds instead of the desired 7 seconds. As this experiment is essential for the modeling, the differing speed was neglected, and instead the TB was adjusted to the actual 7.78 seconds. In this way, the only error that could arise would be from a differing speed perception of the drivers, but as this error was already present in the familiarization drive and speed perception in the driving simulator is limited to visual perception, this is considered to be insignificant.

**Data Inconsistency and Adjustments of Output Variables:**

- Among other variables, the longitudinal acceleration induced by the driver was assessed. When there was no braking input, *Long.Acc.* was set to $0\,m/s^2$. For this reason, small drag torques were not taken into account, as drivers' performance rather than vehicle characteristics are of interest. In those experiments in which automated braking was applied, the recording of *Long.Acc.* started after the automated brake application, which lasted 1.8 seconds, was completed, or as soon as the driver's deceleration exceeded the automated braking. In this way, no other longitudinal accelerations, except those generated by the driver, were considered.

- For measuring *Take-OverTime* (see Subsection 2.6.4.1), a threshold of a 2-degree steering wheel angle had to be exceeded. This did not happen in one take-over, although the participant successfully managed to change lanes. In this case, *Take-OverTime* was manually determined by the progression of the steering wheel angle.
- As the simulation did not feature a reverse gear, in three cases, participants who braked and came to a full stop right in front of the obstacle found themselves in a dead-lock situation, as they were too close to pass the obstacle without colliding. In this case, the participants had to drive through the obstacle to proceed the experimental drive. This intentional collision was not considered in the data. The minimal *TTC* was recorded within the time frame previous to the stopping of the participants' vehicle.
- In the driving environment of the Institute of Ergonomics, the left lane was edged by a small step similar to a curbstone. When this is touched, the simulation software records unrealistic lateral peak accelerations of up to 22 $m/s^2$ for parts of a second. In four cases, these outliers of *Lat.Acc.* had to be removed from the data and replaced by values manually identified by the progression of lateral accelerations.
- In a further six situations, *Lat.Acc.* was not recorded due to an error in the software. For these situations, the lateral accelerations could be subsequently calculated by differentiating vehicles' coordinates.
- In the driving environment of the Institute of Ergonomics, sidewise collisions with vehicles in the neighboring lane did not impact the *TTC*. Therefore, in five situations, the *TTC* was set to zero as the ego-vehicle had contact with a vehicle in the neighboring lane. In this way, a collision is consistently represented by a *TTC* of zero seconds.

The final data-set contains 753 take-overs from 203 different participants, with a complete description of all attributes. As regression analysis requires a metrically scaled input, the ordinal / nominal variables *Lane*, *EyesOffRoad* and *Load* have to be encoded. For *Lane*, the lanes were numbered from 1 (right lane) to 3 (left lane). Another way would be to encode each lane as a separate binary variable. As this could lead to correlations within the data, this coding was rejected. *EyesOffRoad* was implemented as a binary variable with 0 for "eyes on road" and 1 for "eyes off road". Encoding *Load* is more elaborate, as the different tasks have to be ordered regarding their influence on the take-over performance. Retrieving an order from literature is hardly feasible, as sufficient data only exist for manual driving, and transferability of those data to automated driving is at least questionable. As an alternative, the different tasks were rated regarding their manual and cognitive demand as listed in Table 4.3. This does not necessarily have to correlate with take-over performance, which is why comparable data points from the experiments (time budget 7 seconds and 7.78 seconds; traffic density 0 vehicles/km) were plotted over the tasks to support this rating in the context of take-over performance. Data showed a higher impairment of take-over performance in the no-task conditions,

Table 4.3: Rating of tasks regarding their manual and cognitive load.

| Task | Manual Load | Cognitive Load | Total | Encoding |
|---|---|---|---|---|
| None | 0 | 0 | 0 | 1 |
| 20 Questions | 0 | 3 | 3 | 0 |
| SURT | 3 | 0 | 3 | 2 |
| N-Back | 0 | 9 | 9 | 3 |
| Text | 3 | 6 | 9 | 4 |
| Manual Task | 9 | 3 | 12 | 5 |

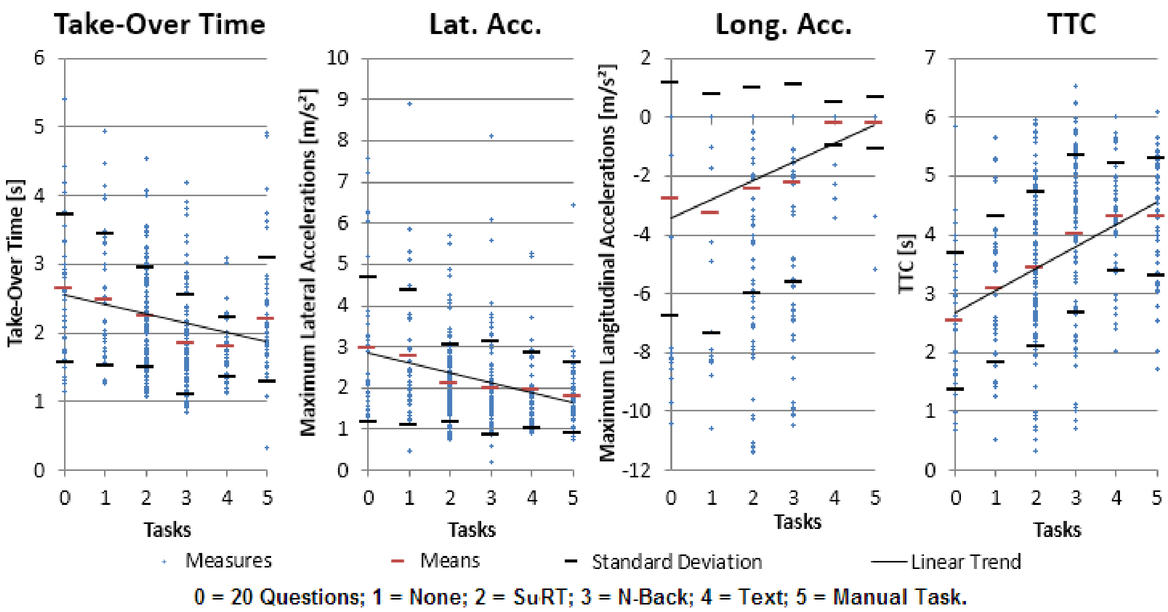



Figure 4.4: Dependent variables over tasks; only data-points with a *TimeBudget* of 7 and 7.78 seconds and *TrafficDensity* = 0 vehicles/km. SuRT (2) and Text (4) are EyesOffRoad-Tasks.

compared to the 20-Questions task. This would be in line with results of Neubauer et al. (2012), who measured quicker brake reactions when subjects were engaged in a phone-task compared to the no-task condition in a take-over situation. Therefore, contrary to Table 4.3, the 20-Questions task was considered to be the lowest load condition (=0) and the no-task condition second (=1). The charts are shown in Figure 4.4 and indicate a linear influence of the ordered tasks. A discussion of the tasks, their influence and the selected order is given in reference to the results of the modeling in Section 4.7.

## 4.3 Multicollinearity

While preparing and reviewing the data-set, multicollinearity was detected. Figure 4.5 provides a correlation table of the different predictors which were used for the modeling approach. There are different suggestions for what correlations indicate serious problems due to collinearity, ranging from 0.35 up to 0.9 (Mason & Perreault, 1991). This thesis follows the rather conservative suggestions by Dormann et al. (2013) and Montgomery and Peck (1992) that correlations above 0.5 should be considered as potentially influencing the results. With this boundary value, four significant correlations were found, three of them involving the *TimeBudget*:

- *TimeBudget* & *AutoBrake* ($r = -.68$)
  The strongest correlation is found between the *TimeBudget* and *AutoBrake*. This correlation is explained by a limited combination of independent variables (predictors) in the experiments. For example, *AutoBrake* was only applied together with a TB of 5 seconds.
- *TimeBudget* & *Repetition* ($r = .59$)
  The second strongest correlation exists between the *TimeBudget* and *Repetition*. Again, insufficient permutation of independent variables is the cause for this strong correlations. High repetitions were measured in one experiment with a TB of 7.78 seconds, whereas repetitions between 2 and 4 were measured with TBs of 5 and 7 seconds.
- *TimeBudget* & *EyesOffRoad* ($r = -.50$)
  The *TimeBudget* further shows correlations with *EyesOffRoad*. Once more, permutation of variables caused this correlation. A TB of 5 seconds was only tested with eyes off road, but not with eyes on road.
- *Load* & *Repetition* ($r = .58$)
  Similar issues lead to a correlation between *Repetition* and *Load*, as several tasks were only tested in the experiment with high repetitions, while others appeared solely in experiments with low repetitions.

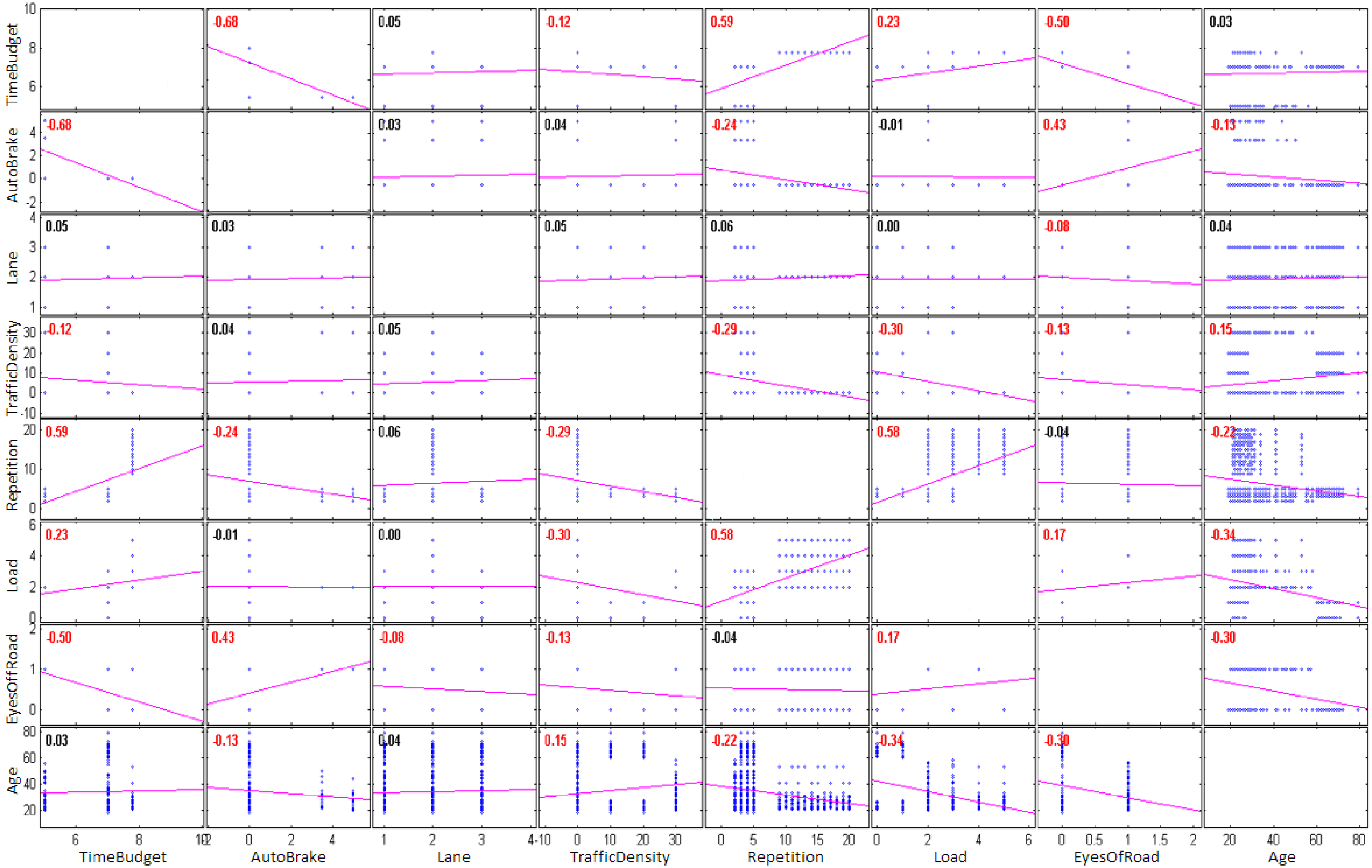



Figure 4.5: Correlation between explanatory variables.

### Methods of Reducing Collinearity

The collinearity in the data has been reduced by combining *TimeBudget* and *AutoBrake*. The main effect of the automated brake maneuver is the extension of the TB. This extension is added to the *TimeBudget* assuming a completely automated brake application of 1.8 seconds, and the explanatory variable *AutoBrake* is removed from the data-set. A TOR of 5 seconds prior to the limit with an automated braking that adds 1 second to the *TimeBudget* is treated like a TOR with a 6-seconds TB from the start. In this way, possible effects arising due to other consequences of *AutoBrake* than an additional TB are neglected, but the models gain in validity and reliability due to a significant reduction of collinearity. Thus, *AutoBrake* could induce a more urgent warning and therefore quicker responses (Gold et al., 2014), but it did not show significant effects on *GazeReactionTime* in the corresponding dynamic driving simulator study (Gold et al., 2014), and an integration of *AutoBrake* into *TimeBudget* appears to be reasonable and completely legitimate, especially as the *TimeBudget* did not show strong effects in the experiment.

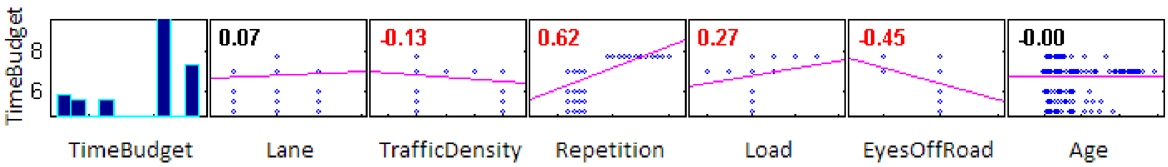



Figure 4.6: Correlation between *TimeBudget* and the other explanatory variables with *AutoBrake* included in *TimeBudget*.

### Evaluation of Remaining Collinearity

The remaining correlations above the 0.5 threshold that should be considered as a possible source of multicollinearity are *TimeBudget* & *Repetition* $(r = .62)$ and *Load* & *Repetition* $(r = .58)$. Both are most likely caused by the permutation of the variables, but the magnitude of the correlations is not regarded as severe for the modeling process, as some authors suggest significantly higher thresholds of 0.7 or 0.9 (Mason & Perreault, 1991). Regarding the VIF score (Table 4.4) of the resulting explanatory variables, which is considered “an overall indication of collinearity” (Belsley et al., 1980, p. 93), the *TimeBudget*, *Repetition*, and *Load* show slightly increased values. Rules of thumb suggest 5 to 10 (Montgomery & Peck, 1992) as a threshold for the indication of relevant collinearity. None of the VIF of the current data-set comes even close to this threshold, which is why multicollinearity is not considered to be an important influencing factor for the following regression analysis, but is still kept in mind for the subsequent interpretations and discussion of the models.

Table 4.4: VIF of variables with *AutoBrake* included in *TimeBudget*.

| | *TimeBudget* | *Lane* | *Traff.Dens.* | *Repetition* | *Load* | *EOR* | *Age* |
|---|---|---|---|---|---|---|---|
| VIF | 2.333 | 1.015 | 1.144 | 2.511 | 1.702 | 1.581 | 1.227 |

## 4.4 Regression Equations

Below, the different regression equations[1] are listed, the process of setting up the equations is described, followed by a short discussion of parameters and the resulting model. In most cases, finding the regression equations and choosing the appropriate regression method is an iterative process (Montgomery & Peck, 1992) that should be explained, which is why preliminary results as steps toward the final model are detailed in this chapter as well. Some general assumptions were made when setting up the equations, which were derived from perception and cognition theory (Section 2.2) and take-over research (Section 2.6).

**Assumptions:**

- Skill levels and training quicken processing speed, response selection and response execution. The corresponding factor *Repetition*, similar to the theory of learning effects, is assumed to follow a logarithmic trend (Buck, 2006), with fast improvements at the beginning and a flattening, converging behavior with an increasing level of training.
- The combination of experience, training, and age effects leads to an exponential (quadratic) influence of the factor *Age* on performance. Reaction times are known to be age-dependent (Höhne, 1974; Kováč, 1969; Welford et al., 1980) and do not show a linear behavior, as young as well as elderly persons generate longer reaction times compared to persons at an age of between 20 and 40 years (Kováč, 1969; Höhne, 1974). A quadratic influence of the age factor is also in line with the main-accident-perpetrator statistic in road traffic, with higher rates of young and elderly drivers, and a minimum at approximately 45 years (Statistisches Bundesamt, Wiesbaden, 2012).
- The *Lane* factor with its three manifestations right (1), center (2) and left (3) is initially considered quadratic, to ensure a fit through all three data points.
- The *TrafficDensity* influences take-over performance by extending the perception and response selection processes (Figure 2.3).
- The *Load* and *EyesOffRoad* factors influence take-over performance in accordance with attention and resource theory, and arousal (Section 2.2).
- The take-over is characterized by a series of parallel processes, which can be addressed by additive regression models (unlike in the modular additive system).

### 4.4.1 Gaze Reaction Time

The *GazeReactionTime* ($t_R$) is the first reaction shown by participants after the TOR and measured by the first gaze directing away from the non-driving-related task. Therefore,

[1]The calculations were performed in MATLAB R2015b. The code (Appendix D) was based on source code of Javensius Sembiring from the Institute of Flight System Dynamics of the Technical University of Munich, and might still include minor parts of the original code and structure.

$t_R$ is only defined if participants are engaged in a visually distracting task (*EyesOffRoad* $=1$). The data-set was subdivided regarding visual distraction, and only those take-overs were considered for modeling $t_R$ in which participants were actually engaged in a visually distracting task, namely SuRT and Text. This leads to a restricted data-set of 378 take-over situations and a reduced variety of tested explanatory variables. Consequently, *TrafficDensity* has the sampling points 0 and 30 vehicles/km and *Age* varies between 20 and 57 years.

#### Setting up the Regression Equation for Gaze Reaction Time

By definition, the *GazeReactionTime* can only be dependent on predictor variables that do not emerge from the traffic situation, as *GazeReactionTime* is measured before the first gaze to the scenery takes place. This is not true for the second and the following take-overs. Some variables, like the *TimeBudget*, are kept constant for the participants, wherefore for example the urgency arising out of the limited TB can influence subsequent take-overs. For this reason, such situational parameters have to be included in the model, as significant variance may emerge due to this effect. For *TrafficDensity*, there are the two sampling points of 0 and 30 in the relevant data-set, while 30 vehicles/km solely appear in one experiment and within the experiment only once for each of the participants. The high traffic condition could therefore not be anticipated, and *TrafficDensity* is not considered in the regression. This is not the case for visually monitoring participants (whose reactions cannot be considered by the gaze reaction) and *TrafficDensity* could indeed influence the reaction time. This is brought up for discussion but cannot be explained by the current data. *Lane* was varied for the individual subjects, is therefore also not likely to be anticipated and is neglected for the model. The other remaining variables are kept in the equation and can be reasonably expected to influence $t_R$. The *TimeBudget* represents the urgency of a take-over and thus motivates faster reactions. The *Repetition* of the take-over is included, as Krinchik (1969) showed that simple reaction times decrease with the probability of a signal and *Repetition* also represents relevant learning effects. The resulting regression equation is given in Equation 4.15.

$$t_R = \beta_0 + \beta_1 I_{TimeBudget} + \beta_2 \ln I_{Repetition} + \beta_3 I_{Load} + \beta_4(\beta_5 + I_{Age})^2 \tag{4.15}$$

#### Discussion of Parameters for Gaze Reaction Time

Table 4.5 shows the estimated $\beta_i$ including the standard error, t-statistics, p-values and effect sizes. The explanatory variables *TimeBudget*, *Load* and *Age* indicate a significant influence on the model in the expected direction. *Load* and a long (less critical) *TimeBudget* increase *GazeReactionTime*, while the shortest *GazeReactionTime* occurs with participants of medium *Age*, similar to simple reaction times in literature (Kováč, 1969). *Repetition* does not show significant effects. It should be remembered that the predictor *Load* only has two sampling points (SuRT & Text) in this model and that the Text task was only part of one of the experiments. Results should therefore be interpreted carefully. The

Table 4.5: Coefficient estimates for *GazeReactionTime*.

| Coef. | Expl. Var. | Est. | SE | tStat | p-Value | Pearson r | Cohen's d |
|---|---|---|---|---|---|---|---|
| $\beta_0$ | - | .228 | .039 | 5.835 | <.001 | .210 | .429 |
| $\beta_1$ | *TimeBudget* | .028 | .007 | 3.822 | <.001 | .139 | .281 |
| $\beta_2$ | *Repetition* | -.013 | .011 | -1.128 | .260 | .041 | -.083 |
| $\beta_3$ | *Load* | .030 | .010 | 2.891 | .004 | .106 | .212 |
| $\beta_4$ | *Age* | .0002 | .0001 | 2.716 | .007 | .099 | .200 |
| $\beta_5$ | *Age* | -32.940 | 2.025 | -16.264 | <.001 | .513 | -1.195 |

final regression equations with the reduced set of predictors are given in Equation 4.16 and Equation 4.17

### Resulting Regression Equation for Gaze Reaction Time

$$t_R = \beta_0 + \beta_1 I_{TimeBudget} + \beta_2 I_{Load} + \beta_3(\beta_4 + I_{Age})^2 \tag{4.16}$$

$$t_R = 0.249 + 0.023 * I_{TimeBudget} + 0.026 * I_{Load} + 1.81 * 10^{-4} * (I_{Age} - 32.914)^2 \tag{4.17}$$

### Discussion of the Resulting Model for Gaze Reaction Time

Figure 4.7 shows the fitted and measured values and the .95 confidence interval, including variance of both model and data. With $\overline{R}^2 = .109$, the model does not perform much better than predicting the mean of all reaction times, regardless of the predictor variables. The model does not add much value for predicting the *GazeReactionTime* to a TOR. Figure 4.8 displays the contribution of the different explanatory variables to *GazeReactionTime*. *GazeReactionTime* is modeled by a constant fraction of 0.25 seconds, plus the contribution of the influencing factors. Consequently, *Load* (only SuRT and Text could be considered) slightly increases *GazeReactionTime* in a magnitude of up to an additional 0.05 seconds. The same is true for the *TimeBudget* (up to 0.07 seconds), and the contribution of the factor *Age* varies between 0 and 0.04 seconds, with a minimum of $\beta_4$ = 33 years, which matched the observations made in simple reaction-times research. It has to be emphasized that regarding *Age*, only data from persons between 20 and 57 could be used for the modeling with very few participants being 40 years and older. The model is therefore mainly fitted for younger drivers, and the further increase of reaction times above 57 years suggested by Figure 4.8 was extrapolated. It is not validated and likely not to match *GazeReactionTime* for elderly persons.

The normal probability plot of residuals (Figure 4.9, left) shows only few deviations from the normal distribution, indicating a spread that is a little higher than expected. Regarding *Cook's Distance* (Figure 4.9, center), some values stand out. Considering the highest six values, we see outliers in both directions: a high *GazeReactionTime* of 1.0, 0.92 and 0.88 seconds, as well as very low *GazeReactionTime* of 0.08, 0.12 (age=50) and 0.40 seconds (age=57). Video analysis did not show unusual behavior of participants with a high *GazeReactionTime*. With regard to the very small *GazeReactionTime* values, it cannot

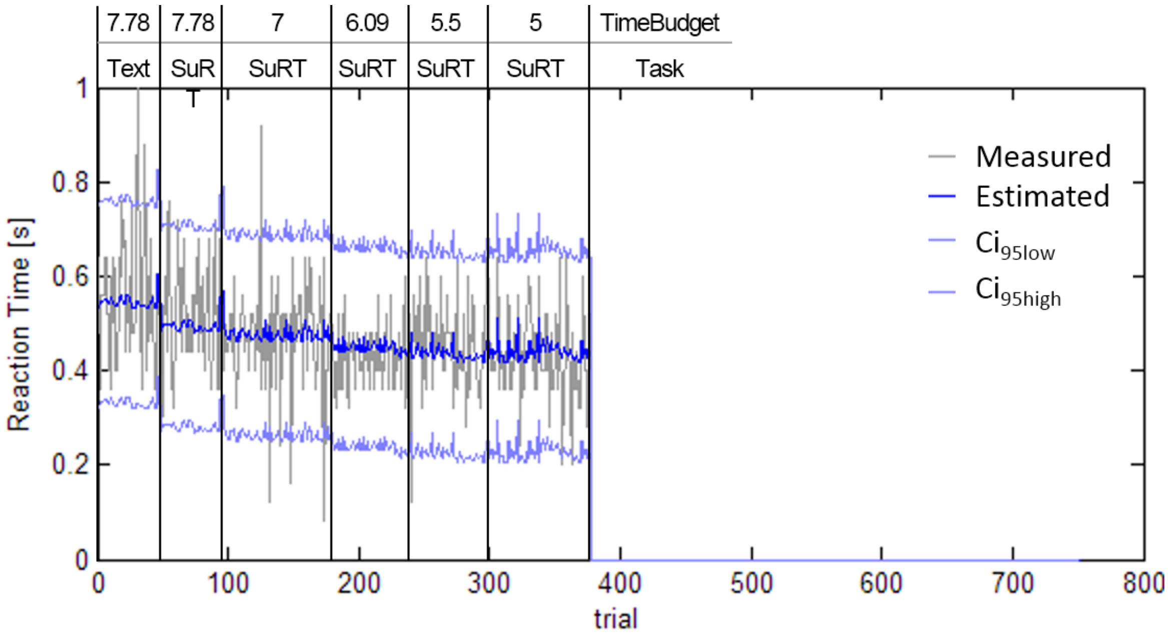



Figure 4.7: Estimation and measures of *GazeReactionTime*.

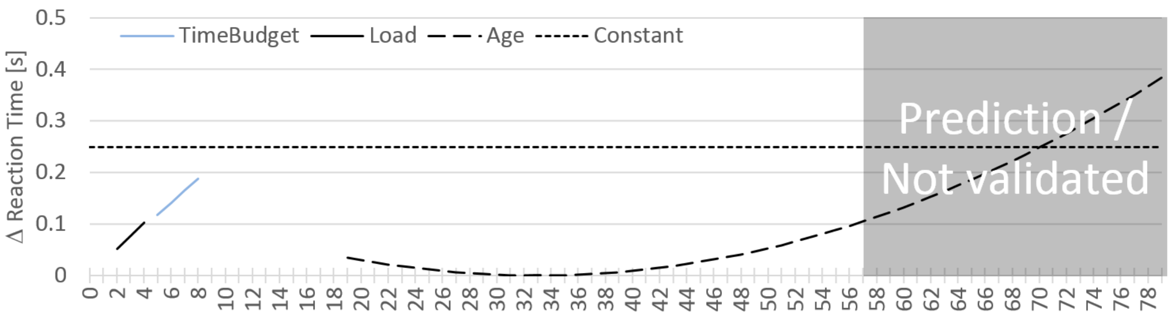



Figure 4.8: Contribution of the different explanatory variables to *GazeReactionTime*.

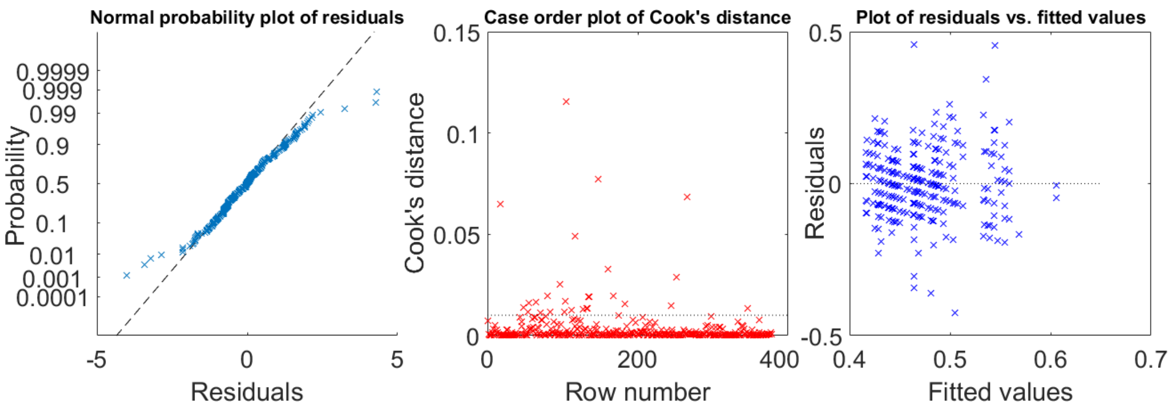



Figure 4.9: Normal probability plot of residuals (left), Cook's Distance (middle) and plot of residuals vs. fitted values (right) for *GazeReactionTime*.

be ruled out that those quick glances were random control glances to the scenery rather than reactions to the TOR. As the explanatory variables are not continuous but disjoint, the plot of residuals (Figure 4.9, right) shows that estimations are also disjoint as only a limited measured combination of predictors' sampling points exist. Besides, the residuals seem to be equally distributed and the quality of prediction is not dependent on the magnitude of the predicted *GazeReactionTime*.

**Summary:** In total, *GazeReactionTime* varies within a comparatively narrow distribution (for normal distribution: $\mu = .469s$; $\sigma = .114s$) with a mean of 0.47 seconds, which calls into question the necessity of a more detailed and elaborate modeling approach. According to the model, the SuRT leads to reactions that are 0.05 seconds faster than those with the Text task. With a similar magnitude, a TB of 5 seconds decreases the *GazeReactionTime* by 0.07 seconds when compared to a TB of 7.78 seconds. The fastest reactions are shown by participants between 28 and 38 years of age, whereas younger and older drivers generate a longer (by up to 100 ms) *GazeReactionTime*.

### 4.4.2 Take-Over Time

The *Take-OverTime* was measured between the TOR and the start of the maneuver, defined by the point at which a steering wheel angle of two degrees or a braking pedal position of 10% is exceeded (cf. Subsection 2.6.4.1).

#### Setting up the Regression Equation for Take-Over Time

The *Take-OverTime*, as the moment when the participants start their maneuver, includes processes of perception and decision-making, which is why all explanatory variables can be reasonably expected to influence the response. The perception of the situational parameters is likely to be dependent on drivers' *Age* (Cantin et al., 2009; Bao & Boyle, 2009), the current *Load* of the driver (Makishita & Matsunaga, 2008), and the complexity of the situation due to limited resources (cf. Wickens, 2008a), represented in the studies by *TrafficDensity* and *Lane*. If the drivers have more time to react to the TOR (predictor *TimeBudget*), they intervene later (Gold, Dambock, et al., 2013). On the other hand, if the subject's eyes are on the road prior to the TOR (*EyesOffRoad* $=0$), this could expedite perceptional processes, as some knowledge of the situation could have already been perceived. Additionally, with more training (*Repetition*), decision-making may move from knowledge-based to rule-based behavior (Rasmussen, 1983) and thus shorten the duration of task selection and execution. *TimeBudget* is initially considered linear and based on an exploratory data analysis (cf. Figure 4.10, left). The influence of *EyesOffRoad* and *Load* are considered linear and *Lane* is considered exponential, as described in Figure 4.4 and Section 4.4. The exploratory data analysis revealed that the *Take-OverTime* decreases with very low and very high *TrafficDensity* and a maximum arises with medium *TrafficDensity* (cf. Figure 4.10, center). For drivers' age (cf. Figure 4.10, right), the analysis confirmed the assumption of a quadratic influence of age, with the fastest take-over at medium *Age*, while young and elderly drivers initiate their maneuvers later. Therefore, for *TrafficDensity* and *Age*, exponential behavior is

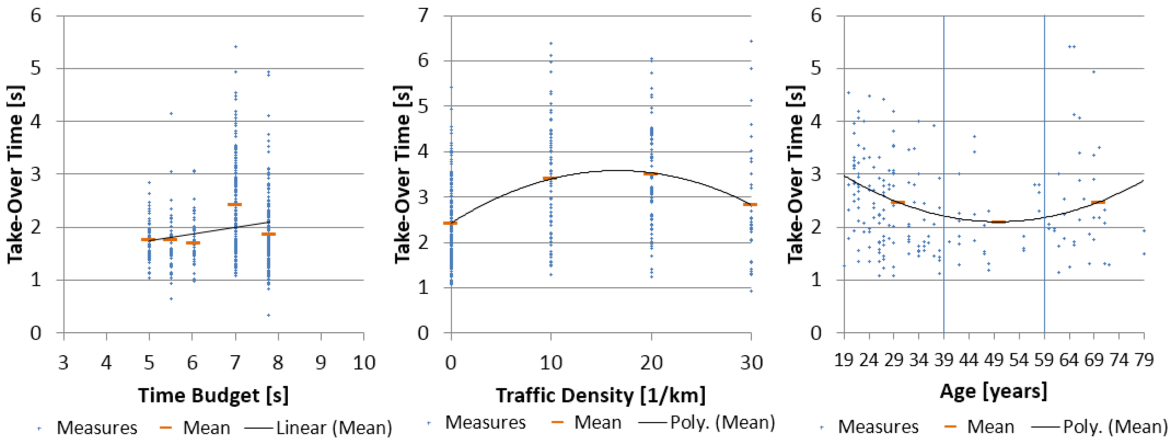



Figure 4.10: Estimated order of selected explanatory variables for modeling *Take-OverTime*, based on a selection of comparable data.

assumed for the modeling. *Repetition* as a representation of the learning effect is considered logarithmic for the previously mentioned reasons. Equation 4.18 summarizes the explanatory variables in form of the initial regression equation.

$$t_T = \beta_0 + \beta_1 I_{TimeBudget} + \beta_2(\beta_3 + I_{Lane})^2 + \beta_4(\beta_5 + I_{TrafficDensity})^2 + \ldots \\ \ldots + \beta_6 \ln I_{Repetition} + \beta_7 I_{Workload} + \beta_8 I_{EOR} + \beta_9(\beta_{10} I_{Age})^2 \tag{4.18}$$

### Discussion of Parameters for Take-Over Time

Table 4.6 shows the estimated $\beta_i$ including standard error, t-statistics, p-values, and effect sizes. The explanatory variables *TimeBudget*, *Lane*, *TrafficDensity*, *Repetition*, and *Age* indicate a significant influence on the model. *Load* and *EyesOffRoad* are not significant and therefore excluded from the resulting regression equation.

Table 4.6: Coefficient estimates for *Take-OverTime*.

| Coef. | Expl. Var. | Est. | SE | tStat | p-Value | Pearson r | Cohen's d |
|---|---|---|---|---|---|---|---|
| $\beta_0$ | - | 2.010 | .369 | 5.452 | <.001 | .196 | .401 |
| $\beta_1$ | *TimeBudget* | .351 | .055 | 6.387 | <.001 | .228 | .469 |
| $\beta_2$ | *Lane* | -.181 | .082 | -2.202 | .028 | .081 | -.162 |
| $\beta_3$ | *Lane* | -2.012 | .132 | -15.283 | <.001 | .490 | -1.123 |
| $\beta_4$ | *TrafficDensity* | -.005 | .001 | -7.377 | <.001 | .262 | -.542 |
| $\beta_5$ | *TrafficDensity* | -15.912 | .498 | -31.925 | <.001 | .761 | -2.346 |
| $\beta_6$ | *Repetition* | -.588 | .075 | -7.813 | <.001 | .276 | -.574 |
| $\beta_7$ | *Load* | -.046 | .038 | -1.228 | .220 | .045 | -.090 |
| $\beta_8$ | *EyesOffRoad* | -.125 | .085 | -1.487 | .142 | .054 | -.108 |
| $\beta_9$ | *Age* | .0001 | .0002 | .616 | .538 | .023 | .045 |
| $\beta_{10}$ | *Age* | -55.561 | 22.415 | -2.479 | .013 | .091 | -.182 |

### Resulting Regression Equation for Take-Over Time

$$\begin{aligned} t_T = \beta_0 + \beta_1 I_{TimeBudget} + \beta_2(\beta_3 + I_{Lane})^2 + ... \\ ... + \beta_4(\beta_5 + I_{TrafficDensity})^2 + \beta_6 \ln I_{Repetition} + \beta_7(\beta_8 + I_{Age})^2 \end{aligned} \tag{4.19}$$

$$\begin{aligned} t_T = 1.826 + 0.378 * I_{TimeBudget} - 0.168 * (I_{Lane} - 2.030)^2 - ... \\ ... - 0.005 * (I_{TrafficDensity} - 15.801)^2 - 0.630 * \ln I_{Repetition} + ... \\ ... + 2.09 * 10^{-4} * (I_{Age} - 47.616)^2 \end{aligned} \tag{4.20}$$

### Discussion of the Resulting Model for Take-Over Time

The model shows a good explanation of variance $\overline{R}^2$=.347, with a RMSE of 0.865 seconds. The two parameters *Load* and *EyesOffRoad* that were expected to influence the *Take-OverTime* did not show significance in the regression analysis, although in the case of *Load*, there were significant differences in the experiments, for example in Experiment 5 (Subsection 3.3.5, (Gold, Berisha, & Bengler, 2015)). The effect may be covered because the *Take-OverTime* is dependent on the subsequent maneuvering and the decisions of the driver for a specific maneuver, which is why the driver contributes a large variance to the data. Collinearity (cf. Section 4.3) to *Repetition* could also cover the effect of *Load* on *Take-OverTime*, although multicollinearity was not considered to seriously influence the modeling (Section 4.3). The significant explanatory variables show small to medium effect sizes and reasonable characteristics. Consequently, as expected, a longer *TimeBudget* leads to later interventions (Gold, Dambock, et al., 2013), and the number of *Repetition* reduces the *Take-OverTime*. The contributions of the different explanatory variables are shown in Figure 4.11. *TrafficDensity* causes a reduced *Take-OverTime* for very low and very dense traffic. The longest *Take-OverTime* is estimated for between 10 and 20 vehicles/km, probably because consideration of an evasive maneuver is the most elaborate, with medium *TrafficDensity* leading to an extended decision-making process. The logarithmic character of *Repetition* indicates a converging in the range of >30 repetitions, based on extrapolation. This saving of time due to training is also responsible for the comparatively short *Take-OverTime* in the group with a TB of 7.78 seconds (Figure 4.12, left), as the *Repetition* variable varies between 9 and 20 in this specific experiment because of additional training in the familiarization drive, which results in a *Take-OverTime* that is 1 to 1.5 seconds shorter. As a negative correlation between *TimeBudget* and *Repetition* became apparent in Section 4.3, both contributions to *Take-OverTime* may vary in magnitude and are possibly smaller than indicated by the model. Statements regarding the magnitude of time-savings due to training have to be treated with care. The explanatory variables *Lane* and *Age* have minor (approx. 0.2 seconds) influence on the *Take-OverTime*. Taking over vehicle control in the center lane slightly increase *Take-OverTime*, possibly because of more potential maneuvers and thus longer choice reaction times (Card et al., 1986). With *Age*, the *Take-OverTime* is slightly higher with young and elderly drivers and shortest with drivers between 40 and 60 years of age, which is in line with the findings from the *GazeReactionTime* model.

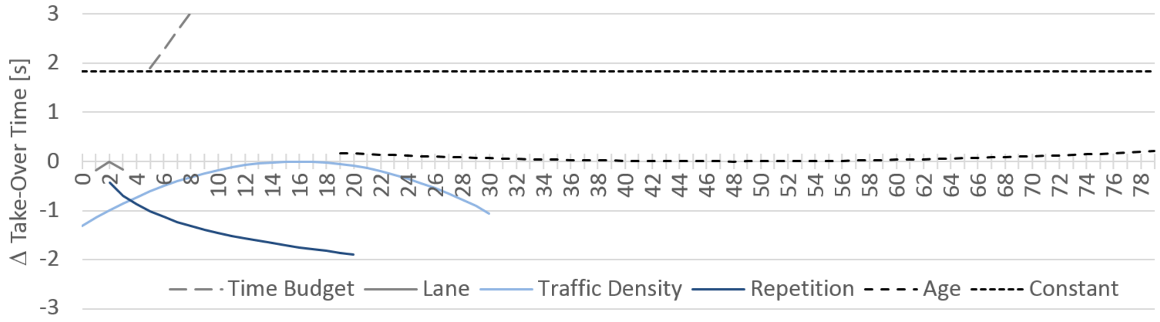



Figure 4.11: Contribution of the different explanatory variables to *Take-OverTime*.

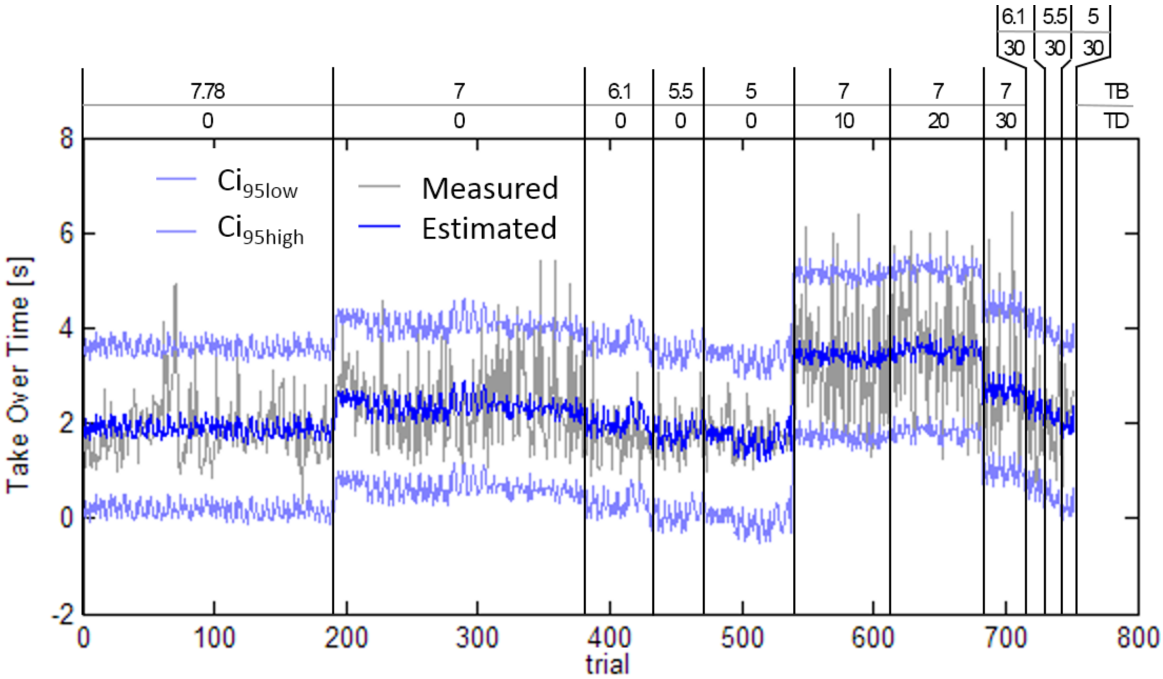



Figure 4.12: Estimation and measures of *Take-OverTime*. TB=Time Budget; TD=Traffic Density.

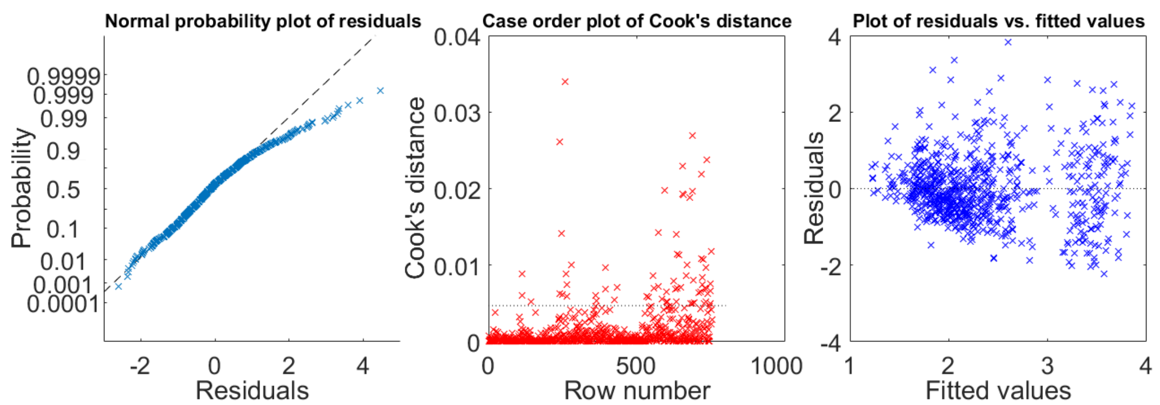



Figure 4.13: Normal probability plot of residuals (left), Cook's Distance (middle) and plot of residuals vs. fitted values (right) for *Take-OverTime*.

The normal probability plot (Figure 4.13, left) indicates a right (positive) skewed distribution, as it is known from human reaction time. Large positive residuals and thus high values of *Take-OverTime* occur more often than expected in normally distributed data.

*Cook's Distance* (Figure 4.13, middle) reveals several data points with an overproportional influence on the model. The outliers are late interventions under the presence of medium to high traffic densities that led to collisions. Considering the six largest values of *Cook's Distance*, one driver changed lanes very late (without applying the brake), four drivers intervened very late and were subsequently involved in a crash, and one driver braked very quickly while the model assumed a rather late intervention. None of them can reasonably be excluded based on video analysis. The right-skewness of the distribution and the influential long *Take-OverTime* point to a rather overestimating behavior of the model, which should be considered when interpreting the data. From a controllability perspective, this bias may be acceptable, as overestimating drivers' *Take-OverTime* would lead to a safer design of the system. The plot of residuals vs. fitted values (Figure 4.13, right) shows a slightly coned shape, indicating that variance is lower in situations with a very small predicted *Take-OverTime*. It further emphasizes the right-skewed distribution, as there seem to be very few outliers on the bottom of the diagram and therefore a border on the left side of the distribution, which reasonably accounts for participants not intervening more quickly than approximately within one second.

**Summary:** The factors *TimeBudget*, *Repetition*, and *TrafficDensity* are the main predictors for the *Take-OverTime*. While elaborate training (*Repetition*) leads to a *Take-OverTime* that is more than one second faster and therefore to a better take-over performance, a medium traffic density as well as longer TBs delay the *Take-OverTime* by more than one second each. The *Lane* and *Age* have minor influence on the *Take-OverTime*, with a slightly slower *Take-OverTime* in the center lane and the fastest *Take-OverTime* at about 48 years of age.

### 4.4.3 Maximum Lateral Acceleration

The maximum lateral acceleration (*Lat.Acc.*), as a measure for take-over quality, was assessed as the peak absolute value of lateral accelerations of the ego-vehicle in the section between the TOR and about 150 meters after passing the obstacle. The exact section is dependent on the particular experiment and its design.

#### Setting up the Regression Equation for Lateral Accelerations

Similar to the *Take-OverTime* (Subsection 4.4.2), all explanatory variables can be reasonably expected to affect *Lat.Acc.* Restricting the available time for a lane-change maneuver by shortening the *TimeBudget* leads to higher accelerations, as the same maneuver has to be performed within less time by increasing lateral speed and thus accelerations. Additionally, *TrafficDensity* is expected to have a major influence on *Lat.Acc.*, as the lane-change behavior of the driver and therefore accelerations should depend on the lane occupancy of the target lane. Figure 4.14 depicts the estimated order of selected explanatory variables, based on a pre-evaluation of parts of the data-set. The

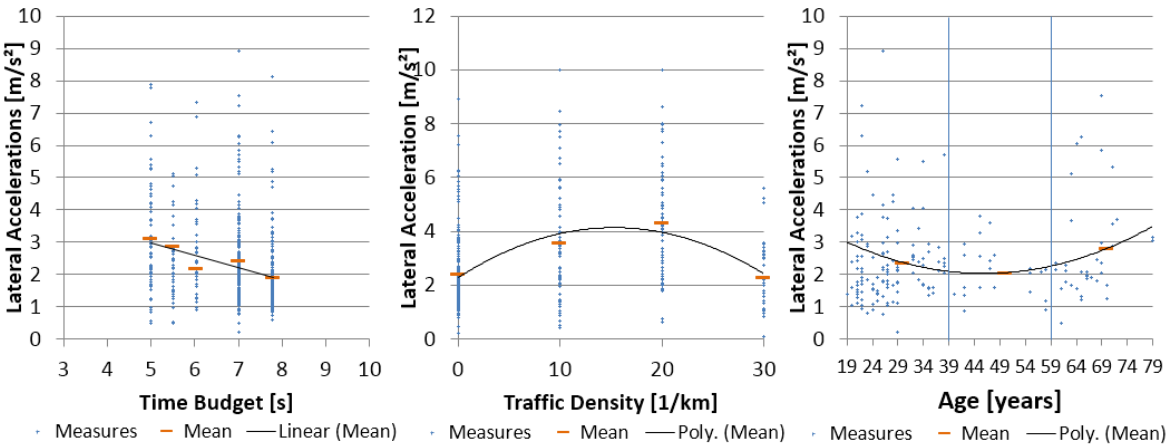



Figure 4.14: Estimated order of selected explanatory variables for modeling *Lat.Acc.*, based on a selection of comparable data.

same behavior for *Lat.Acc.* can be seen as it likewise emerged for the *Take-OverTime* (cf. Figure 4.10). Therefore, the initial modeling approach and equation are identical to Equation 4.18. Preliminary regression results, not separately presented here, indicate a linear rather than quadratic behavior of the *Lane* variable, which is why this simplification is introduced to the model, leading to Equation 4.21.

$$t_T = \beta_0 + \beta_1 I_{TimeBudget} + \beta_2 I_{Lane} + \beta_4(\beta_5 + I_{TrafficDensity})^2 + ... \\ ... + \beta_6 \ln I_{Repetition} + \beta_7 I_{Workload} + \beta_8 I_{EOR} + \beta_9(\beta_{10} I_{Age})^2 \tag{4.21}$$

### Discussion of Parameters for Lateral Accelerations

Table 4.7: Coefficient estimates for *Lat.Acc.*

| Coef. | Expl. Var. | Est. | SE | tStat | p-Value | Pearson r | Cohen's d |
|---|---|---|---|---|---|---|---|
| $\beta_0$ | - | 5.178 | .627 | 8.266 | <.001 | .291 | .607 |
| $\beta_1$ | *TimeBudget* | -.219 | .094 | -2.323 | .020 | .085 | -.171 |
| $\beta_2$ | *Lane* | .245 | .082 | 3.003 | .003 | .110 | .221 |
| $\beta_3$ | *TrafficDensity* | -.007 | .001 | -6.066 | <.001 | .218 | -.446 |
| $\beta_4$ | *TrafficDensity* | -14.487 | .460 | -31.505 | <.001 | .757 | -2.315 |
| $\beta_5$ | *Repetition* | -.278 | .122 | -2.289 | .023 | .083 | -.167 |
| $\beta_6$ | *Load* | -.074 | .064 | -1.152 | .250 | .042 | -.085 |
| $\beta_7$ | *EyesOffRoad* | -.087 | .146 | -0.596 | .551 | .022 | -.044 |
| $\beta_8$ | *Age* | .0008 | .0003 | 2.534 | .012 | .093 | .186 |
| $\beta_9$ | *Age* | -43.720 | 2.412 | -18.128 | <.001 | .554 | -1.332 |

Table 4.7 shows the estimated $\beta_i$ including standard error, t-statistics, p-values, and effect sizes. The predictor variables *TimeBudget*, *TrafficDensity*, *Repetition* and *Age* indicate a significant influence on take-over quality. *Load* and *EyesOffRoad* are not significant and therefore excluded from the regression equation. Again, as *Load* showed correlations to

*Repetition*, this collinearity may have covered parts of the effect of *Load* on the response variable.

### Resulting Regression Equation for Lateral Accelerations

$$\begin{aligned} a_{lat} = \beta_0 + \beta_1 I_{TimeBudget} + \beta_2 I_{Lane} + ... \\ ... + \beta_3(\beta_4 + I_{TrafficDensity})^2 + \beta_5 \ln I_{Repetition} + \beta_6(\beta_7 + I_{Age})^2 \end{aligned} \tag{4.22}$$

$$\begin{aligned} a_{lat} = 5.093 - 0.208 * I_{TimeBudget} + 0.251 * I_{Lane} - ... \\ ... - 0.007 * (I_{TrafficDensity} - 14.500)^2 - 0.341 * \ln I_{Repetition} + ... \\ ... + 9.483 * 10^{-4} * (I_{Age} - 43.071)^2 \end{aligned} \tag{4.23}$$

### Discussion of the Resulting Model for Lateral Accelerations

The model shows a rather low explanation of variance ($\overline{R}^2$=.199) with a RMSE of 1.49 $m/s^2$. The contribution of all explanatory variables considered varies by at least 0.5 $m/s^2$ within the considered range, while *TrafficDensity* (up to 1.7 $m/s^2$) and *Age* (up to 1.2 $m/s^2$) show the largest contribution to *Lat.Acc.* (cf. Figure 4.15). The progression of *TrafficDensity* and *Age* proved a quadratic trend as expected and are similar to *Take-OverTime*. The lowest values occur with medium *TrafficDensity* (14.5 vehicles/km) and *Age* (43 years). For *Age*, this is again in accordance with age effects in simple reaction time research. The other variables, namely *TimeBudget* and *Repetition*, are also plausible regarding their progression and magnitude. *Lane*, which has an unexpected linear behavior, shows increasing accelerations from the right to the left lane with accelerations that are approximately 0.5 $m/s^2$ larger in the left lane. For this characteristic of *Lane*, no explanation in literature could be found. Probably, passing the obstacle on the right side is less common and drivers are not as used to it as to passing on the left (for German drivers, who are not allowed to pass on the right on highways), which is why accelerations may differ depending on the lane. Figure 4.16 also indicates the large influence of *TrafficDensity* on *Lat.Acc.*, which fits the expectations of occupation of the target lane being an important factor when modeling *Lat.Acc.*.

Similar to the *Take-OverTime*, the normal probability plot for *Lat.Acc.* (Figure 4.17, left) shows a distinct positive skew, also apparent when plotting the residuals vs. the fitted values (Figure 4.17, right). There are very few values below 2 $m/s^2$, resulting from the fact that drivers need a certain minimum acceleration to change lanes. In contrast, the distribution shows many measures with high accelerations. Accordingly, outliers identified by *Cook's Distance* (Figure 4.17, middle) are data-points with unexpectedly high *Lat.Acc.* Just like the model for *Take-OverTime*, this indicates that the model rather overestimates the mean lateral accelerations, originating from the skewed distribution and over-proportional influence of outliers in OLS regression.

**Summary:** The factors *TimeBudget*, *Repetition*, *TrafficDensity*, *Age*, and *Lane* are all relevant predictors for *Lat.Acc.* While elaborate training (*Repetition*) and longer TBs lead

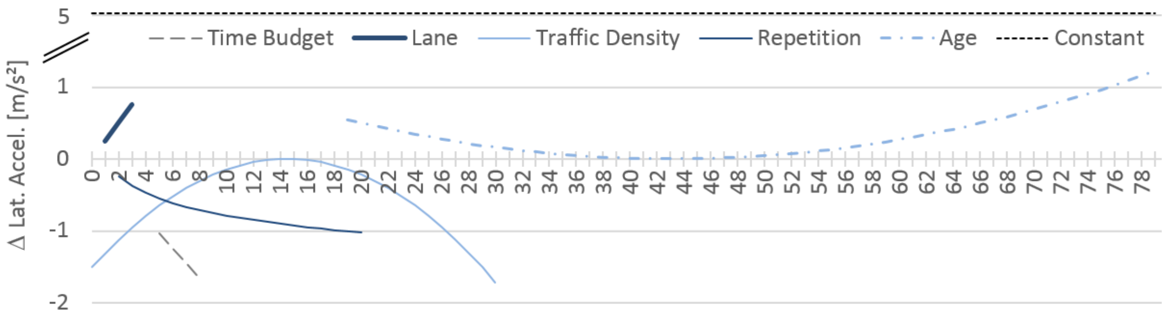



Figure 4.15: Contribution of the different explanatory variables to $Lat.Acc.$ Interrupted ordinate for readability reasons.

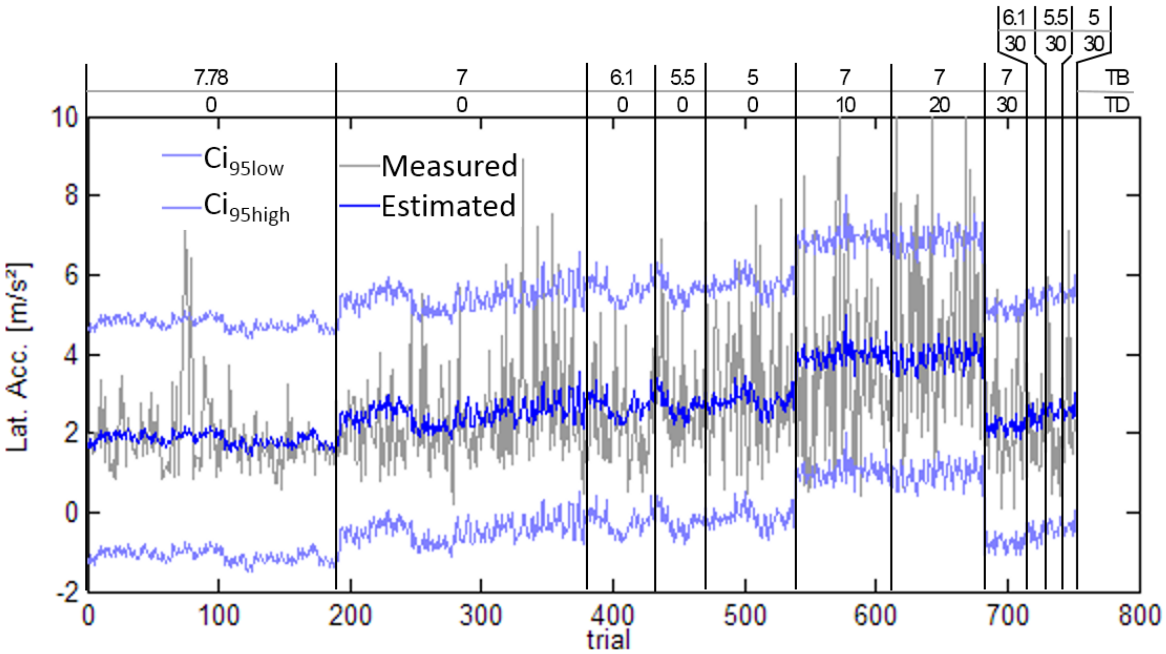



Figure 4.16: Estimation and measures of $Lat.Acc.$ TB = Time Budget; TD = Traffic Density.

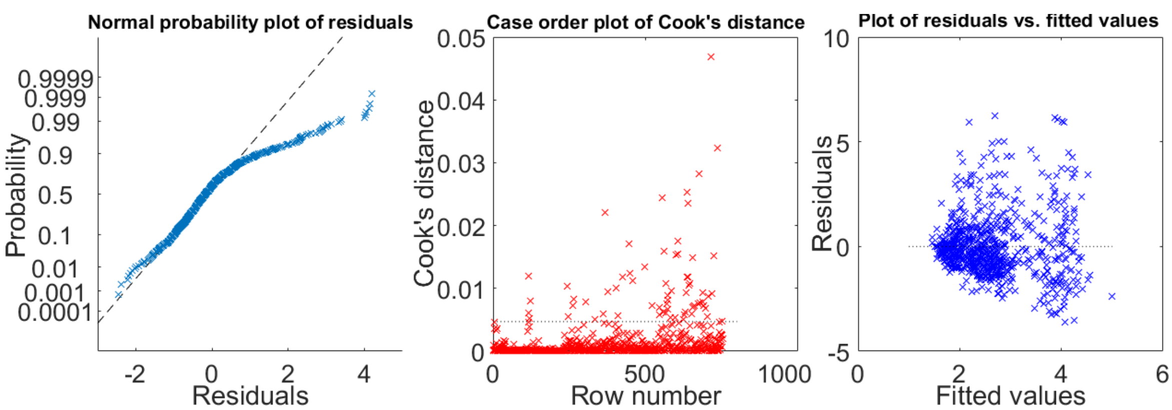



Figure 4.17: Normal probability plot of residuals (left), Cook's Distance (middle) and plot of residuals vs. fitted values (right) for $Lat.Acc.$

to 0.5 to 1 $m/s^2$ lower $Lat.Acc.$ and thus to a better take-over quality, a medium traffic density generates about 1.5 $m/s^2$ higher $Lat.Acc.$, with a maximum at a *TrafficDensity* of 14.5 vehicles/km. The factor *Age*, similar to the *GazeReactionTime* and *Take-OverTime*, showed an improved take-over performance at a medium driver age (43 years of age), with higher accelerations by approximately 1 $m/s^2$ for young and elderly drivers. Additionally, the *Lane* also proved to influence the *Lat.Acc.*, with increasing accelerations from the right to the left lane (magnitude of 0.5 $m/s^2$).

### 4.4.4 Maximum Longitudinal Acceleration

Similar to lateral accelerations, the maximum longitudinal acceleration (*Long.Acc.*) was measured as the peak absolute value of all longitudinal, negative accelerations (braking) of the ego-vehicle in the section between the TOR and about 150 meters after passing the obstacle.

#### Setting up the Regression Equation for Longitudinal Accelerations

Braking and with it *Long.Acc.* can be influenced by different explanatory variables. A shorter *TimeBudget* may lead to a lack of time for the driver's reaction and to a brake application for gaining additional time. Although this effect did not show significance during the experiments (cf. Gold, Dambock, et al., 2013), it is considered a (linear) factor in the regression, as this analysis considers all experiments and, similar to a meta-analysis, could reveal effects that do not emerge in one single experiment. The *TimeBudget* may also be exponential (cf. Figure 4.18), but as no other evidence could be derived from literature or mental models and Figure 4.18 consists of a rather small selection of data points, *TimeBudget* remained to be modeled as linear. Two different types of brake responses interfere in this model, as there are indications that drivers brake in order to gain time for the decision-making process under the presence of traffic (Gold et al., 2014), and, on the other hand, drivers brake in order to stop the vehicle because it is impossible to change to blocked lanes. As driver's age is known to impair the ability to switch tasks (Kray & Lindenberger, 2000) and processing speed (Salthouse, 1991), elderly drivers are expected to show intensified braking in order to compensate for possible limitations, as also indicated by recorded experimental data (Körber et al., 2016). According to the data analysis (cf. Figure 4.18), *Age* and *TrafficDensity* are considered exponential in the regression equation. Following the same argumentation of limited cognitive resources and limited time span for response selection and execution, several other explanatory variables could influence longitudinal accelerations. One of these is the current *Lane*, as drivers have more possible solutions (brake / pass left / pass right) to the TOR in the center lane. Therefore, *Lane* is considered an exponential factor for modeling *Long.Acc.Load* due to a non-driving-related task and with *EyesOffRoad* could further exacerbate the take-over and likewise affect *Long.Acc.*, which is why both variables are considered (as linear terms, cf. Section 4.2) in the equation. On the other hand, experience (*Repetition* logarithmic) could shorten decision-making, possibly making it less necessary to brake in order to gain time for the take-over process. Preliminary regression analysis indicated a linear influence of *Lane*, which is why *Lane* is reduced

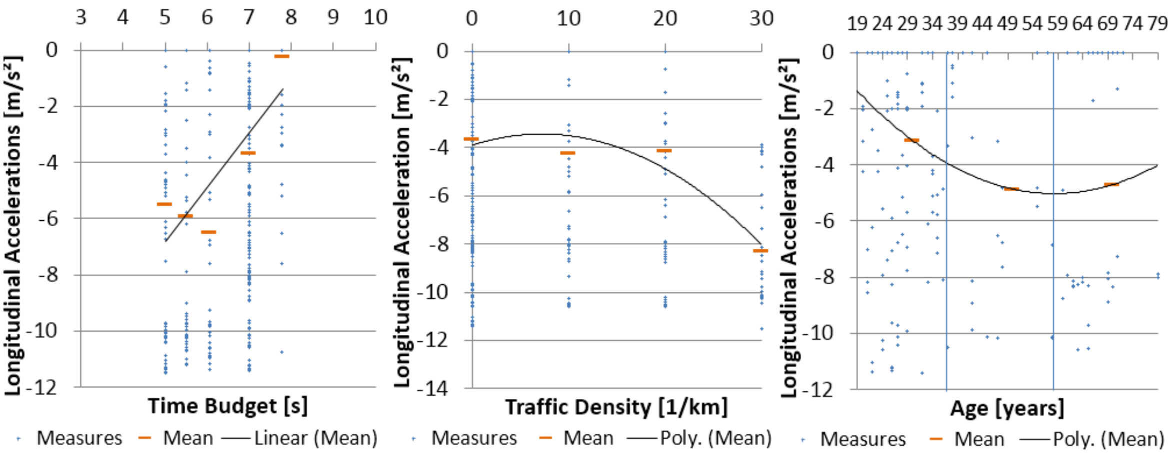



Figure 4.18: Estimated order of selected explanatory variables for modeling *Long.Acc.*, based on a selection of comparable data.

to a linear term. The resulting regression equation is similar to the initial equation for modeling *Lat.Acc.* (Equation 4.21).

### Discussion of Parameters for Longitudinal Accelerations

The variables *Lane*, *Load* and *EyesOffRoad* do not show a significant influence on the model and are excluded from the model approach, leading to the resulting Equation 4.24 and Equation 4.25.

Table 4.8: Coefficient estimates for *Long.Acc.*

| Coef. | Expl. Var. | Est. | SE | tStat | p-Value | Pearson r | Cohen's d |
|---|---|---|---|---|---|---|---|
| $\beta_0$ | - | -15.105 | 1.436 | -10.520 | <.001 | .360 | -.773 |
| $\beta_1$ | *TimeBudget* | 1.254 | .224 | 5.607 | <.001 | .202 | .412 |
| $\beta_2$ | *Lane* | .178 | .194 | .922 | .357 | .034 | .068 |
| $\beta_3$ | *TrafficDensity* | -.005 | .003 | -2.128 | .034 | .078 | -.156 |
| $\beta_4$ | *TrafficDensity* | -2.841 | 5.319 | -.534 | .593 | .020 | -.039 |
| $\beta_5$ | *Repetition* | 1.300 | .290 | 4.486 | <.001 | .163 | .330 |
| $\beta_6$ | *Load* | -.065 | .153 | -.424 | .672 | .016 | -.031 |
| $\beta_7$ | *EyesOffRoad* | -.451 | .347 | -1.300 | .194 | .048 | -.096 |
| $\beta_8$ | *Age* | .001 | .0008 | 1.643 | .101 | .060 | .121 |
| $\beta_9$ | *Age* | -61.744 | 11.901 | -5.188 | <.001 | .187 | -.381 |

### Resulting Regression Equation for Longitudinal Acceleration.

$$a_{long} = \beta_0 + \beta_1 I_{TimeBudget} + \beta_2 * (\beta_3 + I_{TrafficDensity})^2 + \dots \\ \dots + \beta_4 \ln I_{Repetition} + \beta_5(\beta_6 + I_{Age})^2 \tag{4.24}$$

$$\begin{aligned} a_{long} = -15.598 + 1.368 * I_{TimeBudget} - 0.007 * (I_{TrafficDensity} - 5.394)^2 + ... \\ ... + 1.226 * \ln I_{Repetition} + 0.0014(I_{Age} - 58.355)^2 \end{aligned} \tag{4.25}$$

### Discussion of the Resulting Model for Longitudinal Accelerations

The *Long.Acc.* is modeled by an offset of -15.3 $m/s^2$, while *TimeBudget*, *Repetition* and *Age* contribute positive figures and *TrafficDensity* negative ones. The direction of predictors is as expected, as training (*Repetition*) and larger TBs lead to lower accelerations, whereas *TrafficDensity* intensifies braking. Similar to previous models, young and elderly drivers show slightly higher absolute values, with a minimum of *Long.Acc.* at 58 years of age.
The model seems to explain large parts of the variance in the data ($\overline{R}^2$=.345), but this seems to be the case predominantly in very challenging or rather uncritical situations, where the model correctly predicts very high or very low longitudinal accelerations, respectively. Considering Figure 4.20, three classes of situations can be identified: those situations with low demand (left), where very little braking occurred, situations that are very challenging (right), where almost every driver showed full brake applications, and situations with medium demand (middle) where full braking as well as an absence of brake application is observed at the same time, within similar scenarios. The latter induces much variance even under constant preconditions, and is therefore difficult to predict based on the selected predictors. Here, while predictors are basically constant, *Long.Acc.* varies within the full range of 0 to -11 $m/s^2$. This poorer prediction leads to the comparatively high RMSE of 3.53 $m/s^2$. It has to be mentioned that modeling mean values has to generate high residuals with this bimodal distribution, as it models mean brake applications of many trials, but no real brake accelerations of single trials. Insufficient representation of accelerations in the driving simulation may increase bimodality of the distribution and also act a part and increase the number of severe braking maneuvers (McGehee, Mazzae, & Baldwin, 2000). For this reason, the presented model approach may lead to better results and less deviation when predicting performance on the road in real vehicles.

In the distribution of brake accelerations, most weight is located on the ends of the distribution due to the cumulative appearance of full and no-brake applications. This is also the case in the normal probability plot and the plot of residuals vs. fitted values (Figure 4.21, left & right). The normal probability plot indicates a bimodal distribution and two clear borders can be identified in the plot of residuals vs. fitted values, namely of no brake application (upper limit) and full brake application (lower limit). When calculating *Cook's Distance*, six values stand out, among them one measure where no braking occurred, although the situation was very challenging and five measures from participants who were 79 years of age, and who showed severe braking, underestimated by the model and indicating that the factor of age is under-represented when modeling the performance of elderly persons. This is supported by the results of Experiment 6 (Subsection 3.3.6), where higher *Long.Acc.* were measured in the elderly group.

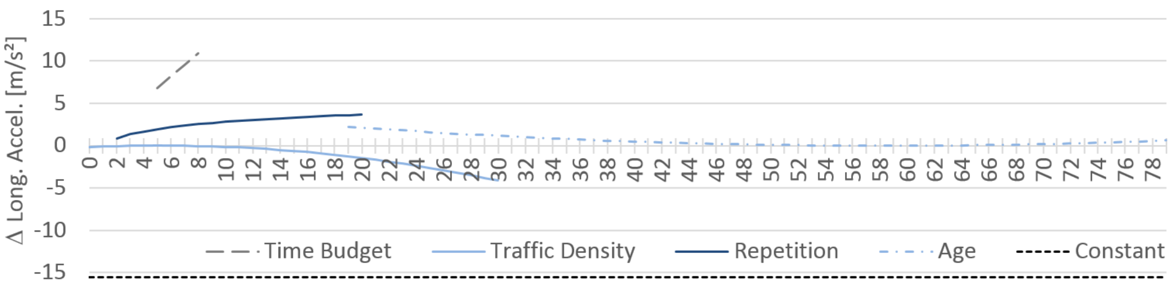



Figure 4.19: Contribution of the different explanatory variables to *Long.Acc.*

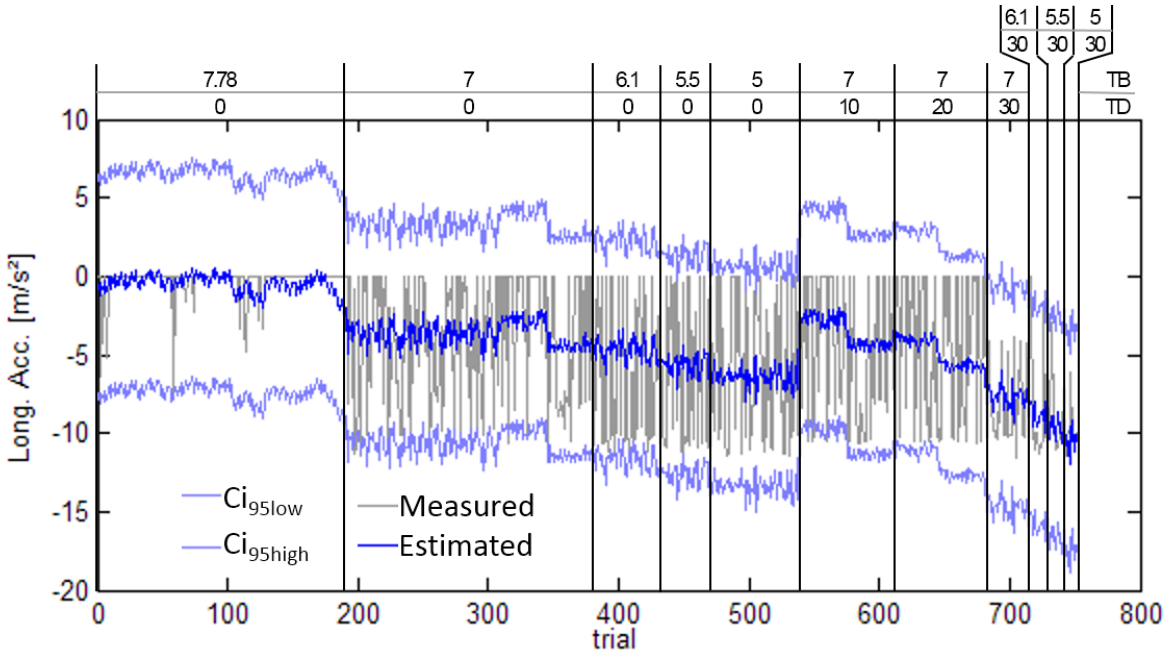



Figure 4.20: Estimation and measures of *Long.Acc.* TB = Time Budget; TD = Traffic Density.

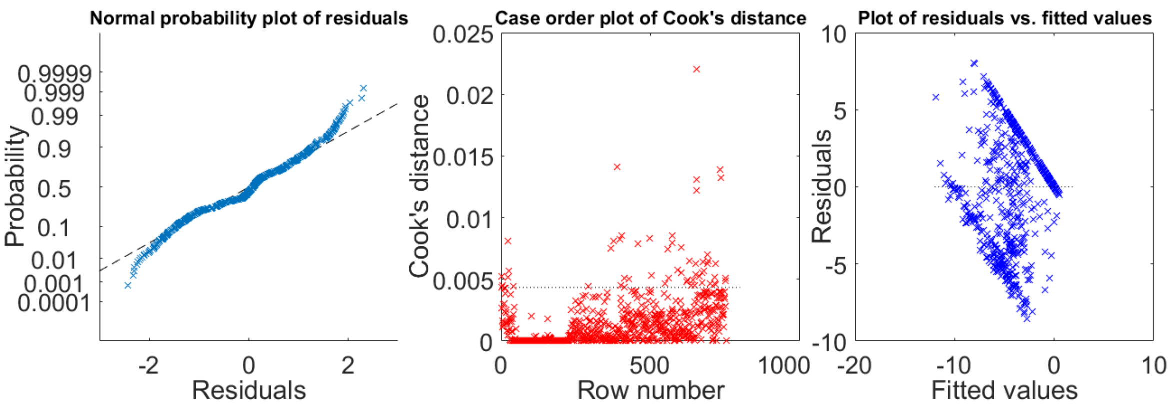



Figure 4.21: Normal probability plot of residuals (left), Cook's Distance (middle) and plot of residuals vs. fitted values (right) for *Long.Acc.*

**Summary:** The factors *TimeBudget*, *TrafficDensity*, *Repetition*, and *Age* influence the *Long.Acc.* A smaller *TimeBudget* as well as a higher *TrafficDensity* lead to a up to 5 $m/s^2$ higher *Long.Acc.* In a similar magnitude, elaborate training of take-over scenarios (*Repetition*) reduces the *Long.Acc.* Elderly and middle-aged drivers induce brake accelerations that are up to 3 $m/s^2$ higher when compared to young drivers. The model's performance is impaired by a non-normal, bimodal distribution of the *Long.Acc.* measures.

### 4.4.5 Minimum Time-to-Collision

The *TTC* was measured as a minimum of all TTC values of the ego-vehicle in the section between the TOR and about 150 meters after passing the obstacle. Collisions are represented by a *TTC* of zero, regardless of whether the participant collided with the obstacle or with vehicles in the neighboring lanes.

#### Setting up the Regression Equation for Time-to-Collision

The *TTC* mathematically depends on the *TimeBudget*, as in the moment of the TOR, the *TTC* equals the *TimeBudget* and decreases until participants brake or change lanes. It is evident that the *TimeBudget* influences the minimum *TTC* and is therefore considered (as a linear factor, cf. Figure 4.22) in the regression equation. Like the other take-over quality metrics, *TTC* is expected to depend on cognitive processing speed and quality of response execution. Therefore, all explanatory variables could impair the *TTC*, namely *Load*, *EyesOffRoad*, *Lane*, *Age*, *TrafficDensity*, and *Repetition*. The latter is considered to be logarithmic, while *Age* and *TrafficDensity* showed exponential behavior in preliminary data analysis (Figure 4.22). A first regression revealed a rather linear influence of *Age*, which is why this factor is considered as such in the equation. *Lane* is considered to be exponential for already mentioned reasons (Section 4.2). The remaining *Load* and *EyesOffRoad* are considered linear for similar reasons as depicted in previous models. See Equation 4.26 for the resulting regression equation.

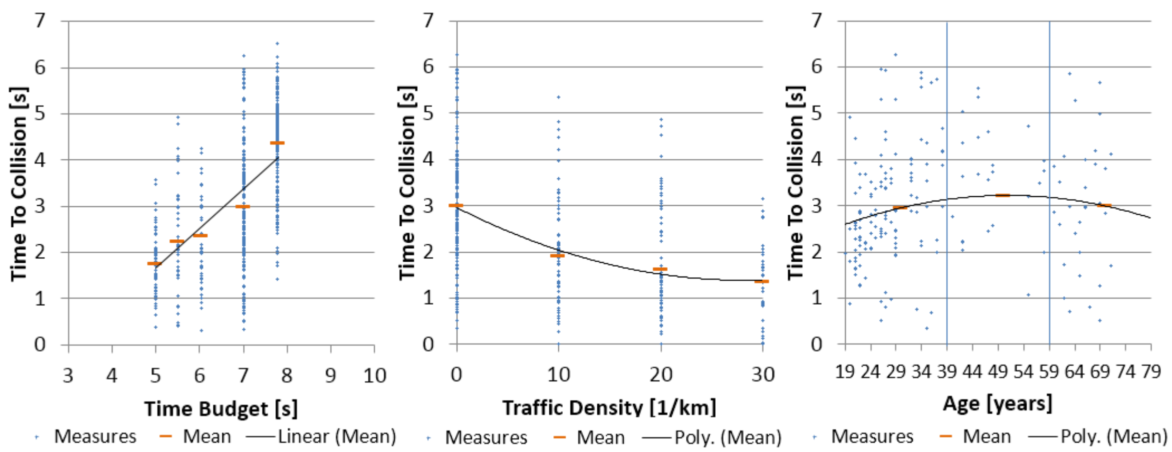



Figure 4.22: Estimated order of selected explanatory variables for modeling *TTC*, based on a selection of comparable data.

$$
\begin{aligned}
t_{TTC} = \beta_0 + \beta_1 I_{TimeBudget} + \beta_2(\beta_3 + I_{Lane})^2 + ... \\
... + \beta_4(\beta_5 + I_{TrafficDensity})^2 + \beta_6 \ln I_{Repetition} + \beta_7 I_{Load} + \beta_8 I_{EOR} + \beta_9 I_{Age}
\end{aligned}
\tag{4.26}
$$

#### Discussion of Parameters for Time-to-Collision

Most of the explanatory variables show a significant influence on the model (cf. Table 4.9). Only *EyesOffRoad* fails the criteria and is excluded from the model. The resulting regression equations are presented in Equation 4.27 and Equation 4.28.

Table 4.9: Coefficient estimates for $TTC$.

| Coef. | Expl. Var. | Est. | SE | tStat | p-Value | Pearson r | Cohen's d |
|---|---|---|---|---|---|---|---|
| $\beta_0$ | - | -3.233 | .453 | -7.131 | <.001 | .253 | -.524 |
| $\beta_1$ | *TimeBudget* | .543 | .069 | 7.917 | <.001 | .279 | .582 |
| $\beta_2$ | *Lane* | -.124 | .103 | -1.208 | .228 | .044 | -.089 |
| $\beta_3$ | *Lane* | -1.499 | .467 | -3.209 | .001 | .117 | -.236 |
| $\beta_4$ | *TrafficDensity* | .002 | .0008 | 2.763 | .006 | .101 | .203 |
| $\beta_5$ | *TrafficDensity* | -25.882 | 4.565 | -5.670 | <.001 | .204 | -.417 |
| $\beta_6$ | *Repetition* | .418 | .094 | 4.457 | <.001 | .162 | .327 |
| $\beta_7$ | *Load* | .174 | .045 | 3.868 | <.001 | .141 | .284 |
| $\beta_8$ | *EyesOffRoad* | -.039 | .106 | -.372 | .710 | .014 | -.027 |
| $\beta_9$ | *Age* | .008 | .003 | 2.778 | .006 | .102 | -.204 |

#### Resulting Regression Equation for Time-to-Collision

$$
\begin{aligned}
t_{TTC} = \beta_0 + \beta_1 I_{TimeBudget} + \beta_2(\beta_3 + I_{Lane})^2 + ... \\
... + \beta_4(\beta_5 + I_{TrafficDensity})^2 + \beta_6 \ln I_{Repetition} + \beta_7 I_{Load} + \beta_8 I_{Age}
\end{aligned}
\tag{4.27}
$$

$$
\begin{aligned}
t_{TTC} = -3.326 + 0.554 * I_{TimeBudget} - ... \\
... - 0.123 * (I_{Lane} - 1.5)^2 + 0.0021 * (I_{TrafficDensity} - 26.420)^2 + ... \\
... + 0.413 * \ln I_{Repetition} + 0.175 * I_{Load} + 0.008 * I_{Age}
\end{aligned}
\tag{4.28}
$$

#### Discussion of the Resulting Model for Time-to-Collision

The $TTC$ model explains half of the variance in the data ($\overline{R}^2$=.509) with quite a low RMSE of 1.081 seconds. The variables *TrafficDensity*, *Repetition*, *TimeBudget*, and *Age* influence the $TTC$ as expected. A high *TrafficDensity* leads to a shorter and therefore more critical $TTC$, converging for a *TrafficDensity* of more than 20 vehicles/km. With the current model, extrapolation for higher traffic densities of more than 30 vehicles/km would lead to a re-increase of the $TTC$, which is not reasonable. A more meaningful way would be to substitute the exponential term by a $1/x$ term, introduced in Equation 4.29. This way a re-increase of the $TTC$ above 30 vehicles/km is prevented and the progression of

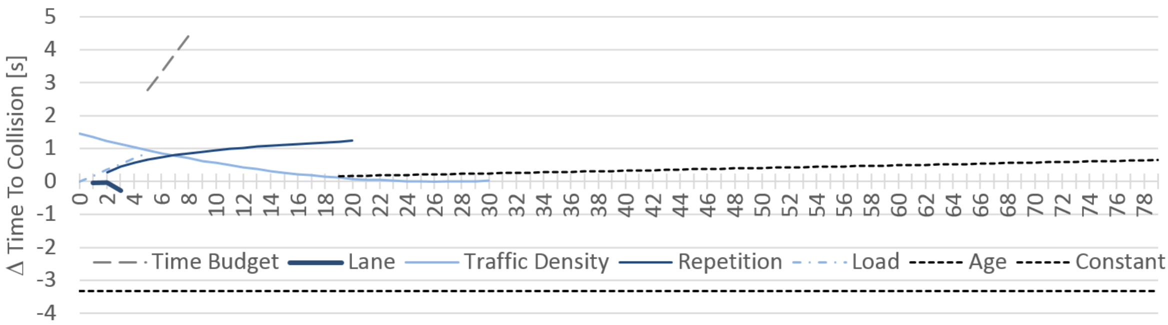



Figure 4.23: Contribution of the different explanatory variables to $TTC$.

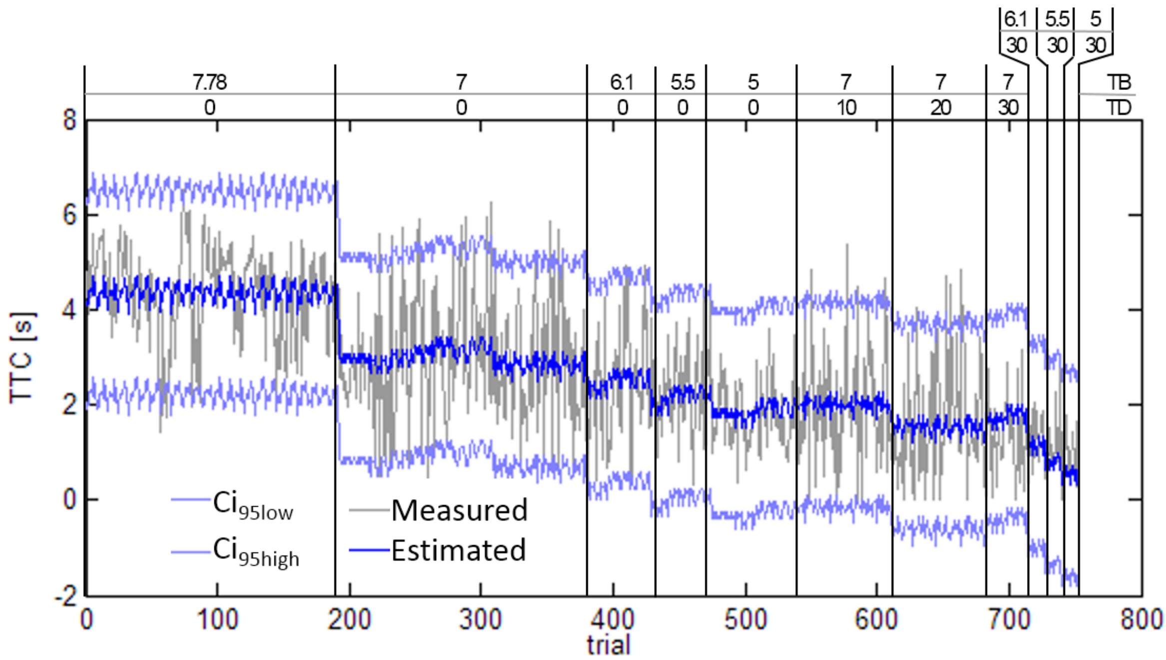



Figure 4.24: Estimation and measures of $TTC$. TB = Time Budget; TD = Traffic Density.

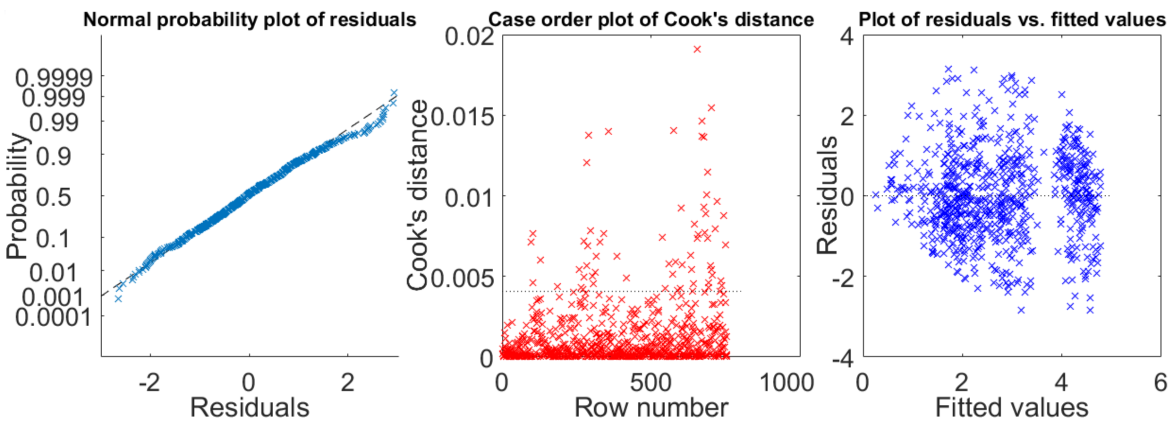



Figure 4.25: Normal probability plot of residuals (left), Cook's Distance (middle) and plot of residuals vs. fitted values (right) for $TTC$.

*TrafficDensity* below 30 vehicles/km remains similar. Training (*Repetition*) and a longer *TimeBudget* increase the *TTC*, while the *TimeBudget* has a strong influence on the *TTC* and a one second longer *TimeBudget* leads to a *TTC* that is almost one second longer within the considered range. This underlines the importance of the *TimeBudget* for safety in take-over scenarios. *Age*, in accordance with Körber et al. (2016), induces more brake reactions and thus a longer *TTC*. The *Lane* shows a slightly shorter *TTC* for the left lane, compared to the middle and right lane, which would fit the slightly higher *Lat.Acc.* in the left lane, identified when modeling *Lat.Acc.* What is unexpected is the influence of *Load*, as tasks considered to be more complex actually lead to a longer *TTC*. This is in accordance with the preliminary data analysis in Figure 4.4 and will be discussed separately in Section 4.7.

$$\begin{aligned} t_{TTC} = -3.771 + 0.554 * I_{TimeBudget} - 0.131 * (I_{Lane} - 1.532)^2 + ... \\ ... + 18.112 * (I_{TrafficDensity} + 9.497)^{-1} + 0.408 * \ln I_{Repetition} + ... \\ ... + 0.174 * I_{Load} + 0.008 * I_{Age} \end{aligned} \tag{4.29}$$

The normal probability plot of residuals indicates an almost perfect normal distribution of the residuals (cf. Figure 4.25, left). The six data points with the highest *Cook's Distance* are consistently long TTC values. For this reason, the model is influenced by those outliers and estimates TTC values that are rather too large. Regarding controllability aspects of the take-over, this should be considered when interpreting the model output, as too high estimations of for TTC could lead to an underestimation of risk. The residuals in the plot of residuals vs. fitted values (cf. Figure 4.25, right) are decently distributed and within normal limits, not suggesting much need for model improvement.

**Summary:** *TimeBudget*, *Repetition*, *TrafficDensity*, and *Age* are the main influencing factors for *TTC*. A shorter *TimeBudget* and a higher *TrafficDensity* evoke a reduction of *TTC* with a magnitude of more than one second, leading to a plain increase of risk in the take-over scenario. Training the take-over (*Repetition*), however, leads to an increased *TTC* and therefore safer take-overs (higher take-over performance). With a rise of driver's age, the *TTC* is also extended (by up to 0.5 seconds), indicating a safer outcome with older drivers.

### 4.4.6 Linearization of the Models

Some of the optimization and subsequent methods require linear models, and the models can be transferred to linear models through data-set transformations. So far, this was avoided to keep interpretability high, but linearization is inevitable for some of the following sections. Exponential terms in the model equation can be linearized according to Equation 4.3. For linearization of the logarithmic *Repetition*, the data is transformed by the logarithmic function $x' = \ln x$. The resulting linearized models are shown in Equation 4.30 to Equation 4.34. The transformation of the data-set is indicated by $^2$ and $'$ in the equations.

$$t_R = 0.444 + 0.023 * I_{TimeBudget} + 0.026 * I_{Load} - 0.012 * I_{Age} + 1.807 * 10^{-4} * I_{Age}^2 \tag{4.30}$$

$$\begin{aligned} t_T = 0.230 + 0.378 * I_{TimeBudget} + 0.683 * I_{Lane} - 0.168 * I_{Lane}^2 + ... \\ ... + 0.165 * I_{TrafficDensity} - 0.005 * I_{TrafficDensity}^2 - 0.630 * I'_{Repetition} - ... \\ ... - 0.020 * I_{Age} + 2.087 * 10^{-4} * I_{Age}^2 \end{aligned} \tag{4.31}$$

$$\begin{aligned} a_{lat} = 5.343 - 0.208 * I_{TimeBudget} + 0.251 * I_{Lane} + ... \\ ... + 0.208 * I_{TrafficDensity} - 0.007 * I_{TrafficDensity}^2 - 0.341 * I'_{Repetition} - ... \\ ... - 0.082 * I_{Age} + 9.483 * 10^{-4} * I_{Age}^2 \end{aligned} \tag{4.32}$$

$$\begin{aligned} a_{long} = -10.885 + 1.368 * I_{TimeBudget} + 0.074 * I_{TrafficDensity} - ... \\ ... - 0.007 * I_{TrafficDensity}^2 + 1.226 * I'_{Repetition} - 0.168 * I_{Age} + 0.001 * I_{Age}^2 \end{aligned} \tag{4.33}$$

$$\begin{aligned} t_{TTC} = -2.158 + 0.554 * I_{TimeBudget} + 0.369 * I_{Lane} - 0.123 * I_{Lane}^2 - ... \\ ... - 0.109 * I_{TrafficDensity} + 0.002 * I_{TrafficDensity}^2 + ... \\ ... + 0.413 * I'_{Repetition} + 0.175 * I_{Load} + 0.008 * I_{Age} \end{aligned} \tag{4.34}$$

### 4.4.7 Nominal Regression for Crash Probability

Apart from the already mentioned measures for take-over performance, crashes in the take-over scenarios occurred unintentionally. A crash is the most severe outcome and can also be considered as a performance or safety metric for take-over scenarios. During the experiments, different crash types occurred, namely head-on collisions with the obstacle due to late or insufficient braking and collisions with vehicles in the neighboring lanes while executing a lane change. There are more conceivable types of collisions, among them rear-end collisions due to strong braking of the drivers, collisions with static obstacles in the surroundings, or loss of control while performing a maneuver with no involvement of other vehicles. It has to be emphasized that a driving simulator is probably not well-suited to derive absolute values such as crash frequencies. For different reasons, the number of crashes in similar scenarios may vary in real traffic. The surrounding traffic, for example, was not cooperative and did not anticipate a possible lane change of the participant. Nevertheless, crashes are considered to be an important relative predictor for take-over quality and must not be neglected when modeling take-over performance.

To model crash probability, the dependent variable *Crash* is introduced. Contrary to previous measures, *Crash* is not metric, which is why a different regression method applies. Nominal variables, like *Crash*, can be modeled by Logistic Regressions, predicting a probability for *Crash* between 0 and 1. The logistic function that is used for the regression is shown in Equation 4.35, while $t$ is a linear function considering the explanatory variables $x_n$ as a linear combination (Equation 4.36).

$$\sigma = \frac{1}{1+e^t} \tag{4.35}$$

$$t = \beta_0 + \beta_1 * x_1 + ... + \beta_n * x_n \tag{4.36}$$

**Setting up the Regression Equation for Crash Probability**

As the predictor variables selected for the modeling approach in this thesis all influence take-over performance, they can also be reasonably expected to influence *Crash*, as longer *Take-OverTime*, shorter TTCs, and higher accelerations make crashes more likely. *TrafficDensity* and *Age* are considered exponential, *Repetition* is considered logarithmic and the other variables *TimeBudget*, *Load* and *EyesOffRoad* linear (cf. Equation 4.37). Due to the limited permutation within the training data, 28 out of 35 crashes occurred in the center lane. For this reason, the variable *Lane* was not considered for modeling *Crash*, in order to avoid a biased estimation.

$$\begin{aligned} t = \beta_0 + \beta_1 I_{TimeBudget} + \beta_2 I_{TrafficDensity} + \beta_3 I^2_{TrafficDensity} + ... \\ ... + \beta_4 I'_{Repetition} + \beta_5 I_{Load} + \beta_6 I_{EOR} + \beta_7 I_{Age} + \beta_8 I^2_{Age} \end{aligned} \tag{4.37}$$

Table 4.10 displays results of the nominal regression. Successively eliminating insignificant factors with small effect sizes leads to the three significant predictor variables *TrafficDensity* ($p$<.001), *TrafficDensity* $^2$ ($p$=.002) and *Repetition* ($p$=.046) in the final regression equations Equation 4.38 and Equation 4.39.

Table 4.10: Coefficient estimates for *Crash* Probability.

| Coef. | Expl. Var. | Est. | SE | tStat | p-Value | Pear. r | Cohen's d |
|---|---|---|---|---|---|---|---|
| $\beta_0$ | - | 7.994 | 3.310 | 2.415 | .016 | .088 | .177 |
| $\beta_1$ | *TimeBudget* | -.512 | .313 | -1.637 | .102 | .060 | -.120 |
| $\beta_2$ | *TrafficDensity* | -.414 | .203 | -2.039 | .041 | .075 | -.150 |
| $\beta_3$ | *TrafficDensity* $^2$ | .009 | .007 | 1.333 | .183 | .049 | .098 |
| $\beta_4$ | *Repetition* | 1.366 | .641 | 2.131 | .033 | .078 | .157 |
| $\beta_5$ | *Load* | .104 | .465 | .223 | .824 | .008 | .016 |
| $\beta_6$ | *EyesOffRoad* | -1.064 | .885 | -1.201 | .230 | .044 | -.088 |
| $\beta_7$ | *Age* | -.015 | .104 | -.146 | .884 | .005 | -.011 |
| $\beta_8$ | *Age* $^2$ | .0002 | .001 | .210 | .884 | .008 | .015 |

### Resulting Regression Equation for Crash Probability

$$\sigma_{Crash} = \frac{1}{1 + e^{\beta_0 + \beta_1 I_{TrafficDensity} + \beta_2 I^2_{TrafficDensity} + \beta_3 I_{Repetition}}} \quad (4.38)$$

$$\sigma_{Crash} = \frac{1}{1 + e^{4.108 - 0.360 * I_{TrafficDensity} + 0.007 * I^2_{TrafficDensity} + 1.275 * I_{Repetition}}} \quad (4.39)$$

### Discussion of the Resulting Model for Crash Probability

Figure 4.26 shows the contribution of the explanatory variables to $t$ and thus (inverted) to *Crash*. *TrafficDensity* and *Repetition* have a large influence, similar in magnitude, but not in direction. While *Repetition* reduces the crash probability, *TrafficDensity* increases *Crash* with a maximum at about 25 vehicles/km, similar to previous models. As only two predictors determine *Crash*, the resulting probability can be displayed in a two-dimensional matrix (Figure 4.27). Higher *Crash* probabilities are marked in red, lower ones in green. The values in column one (*Repetition* = 1) are extrapolations, as there were no take-overs in the data for which the subjects had not experienced at least one take-over before the experimental drive. Figure 4.28 shows the estimation and measures of *Crash*. For depiction, data was sorted by ascending predicted *Crash* probability, and the binomial measure of crash occurrence *Crash* was averaged over 50 data points to derive a frequency that can be compared to the model's predictions. Furthermore, the Receiver Operator Characteristic (ROC) curve is presented in Figure 4.28. The ROC curve plots the true positive rate against the false positive rate. A random performance of the model would be represented by a diagonal line from (0,0) to (1,1), whereas ROC curves of good models approach the upper left corner. The Area Under the Curve (AUC) is an important statistical property and "is equivalent to the probability that the classifier will rank a randomly chosen positive instance higher than a randomly chosen negative instance" (Fawcett, 2006, p. 872). With an AUC of $> 0.9$, the model for *Crash* can be considered to show high accuracy (Swets, 1988), and the estimated probabilities also fit the measures.

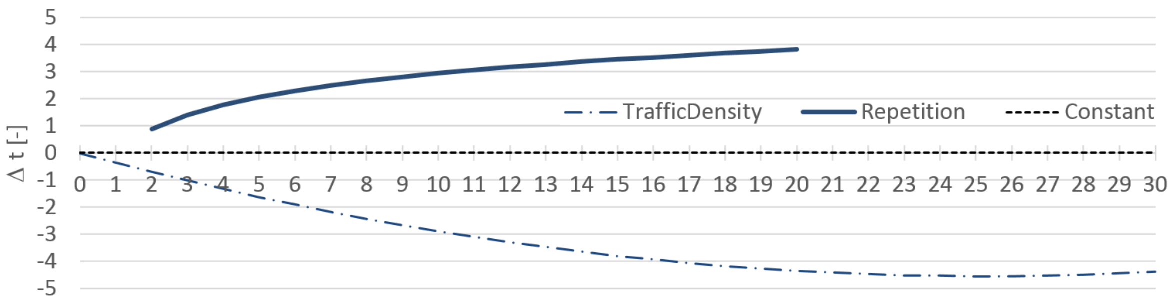



Figure 4.26: Contribution of the different explanatory variables to t for estimating *Crash* Probability.

| Traffic Density \ Repetition | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 0.016 | 0.007 | 0.004 | 0.003 | 0.002 | 0.002 | 0.001 | 0.001 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 1 | 0.023 | 0.010 | 0.006 | 0.004 | 0.003 | 0.002 | 0.002 | 0.002 | 0.001 | 0.001 | 0.001 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 2 | 0.032 | 0.013 | 0.008 | 0.006 | 0.004 | 0.003 | 0.003 | 0.002 | 0.002 | 0.002 | 0.002 | 0.001 | 0.001 | 0.001 | 0.001 | 0 | 0 | 0 | 0 | 0 |
| 3 | 0.043 | 0.018 | 0.011 | 0.008 | 0.006 | 0.005 | 0.004 | 0.003 | 0.003 | 0.002 | 0.002 | 0.002 | 0.002 | 0.002 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0 |
| 4 | 0.058 | 0.025 | 0.015 | 0.010 | 0.008 | 0.006 | 0.005 | 0.004 | 0.004 | 0.003 | 0.003 | 0.003 | 0.002 | 0.002 | 0.002 | 0.002 | 0.002 | 0.002 | 0.001 | 0.001 |
| 5 | 0.077 | 0.033 | 0.020 | 0.014 | 0.011 | 0.008 | 0.007 | 0.006 | 0.005 | 0.004 | 0.004 | 0.003 | 0.003 | 0.003 | 0.003 | 0.002 | 0.002 | 0.002 | 0.002 | 0.002 |
| 6 | 0.099 | 0.044 | 0.026 | 0.019 | 0.014 | 0.011 | 0.009 | 0.008 | 0.007 | 0.006 | 0.005 | 0.005 | 0.004 | 0.004 | 0.003 | 0.003 | 0.003 | 0.003 | 0.003 | 0.002 |
| 7 | 0.126 | 0.056 | 0.034 | 0.024 | 0.018 | 0.014 | 0.012 | 0.010 | 0.009 | 0.008 | 0.007 | 0.006 | 0.005 | 0.005 | 0.005 | 0.004 | 0.004 | 0.004 | 0.003 | 0.003 |
| 8 | 0.157 | 0.071 | 0.044 | 0.031 | 0.023 | 0.019 | 0.015 | 0.013 | 0.011 | 0.010 | 0.009 | 0.008 | 0.007 | 0.006 | 0.006 | 0.005 | 0.005 | 0.005 | 0.004 | 0.004 |
| 9 | 0.191 | 0.089 | 0.055 | 0.039 | 0.029 | 0.023 | 0.019 | 0.016 | 0.014 | 0.012 | 0.011 | 0.010 | 0.009 | 0.008 | 0.007 | 0.007 | 0.006 | 0.006 | 0.005 | 0.005 |
| 10 | 0.228 | 0.109 | 0.068 | 0.048 | 0.037 | 0.029 | 0.024 | 0.020 | 0.018 | 0.015 | 0.014 | 0.012 | 0.011 | 0.010 | 0.009 | 0.009 | 0.008 | 0.007 | 0.007 | 0.006 |
| 11 | 0.267 | 0.131 | 0.082 | 0.059 | 0.045 | 0.036 | 0.030 | 0.025 | 0.022 | 0.019 | 0.017 | 0.015 | 0.014 | 0.012 | 0.011 | 0.011 | 0.010 | 0.009 | 0.008 | 0.008 |
| 12 | 0.307 | 0.155 | 0.099 | 0.070 | 0.054 | 0.043 | 0.036 | 0.030 | 0.026 | 0.023 | 0.020 | 0.018 | 0.017 | 0.015 | 0.014 | 0.013 | 0.012 | 0.011 | 0.010 | 0.010 |
| 13 | 0.347 | 0.180 | 0.116 | 0.083 | 0.064 | 0.051 | 0.043 | 0.036 | 0.031 | 0.027 | 0.024 | 0.022 | 0.020 | 0.018 | 0.017 | 0.015 | 0.014 | 0.013 | 0.012 | 0.012 |
| 14 | 0.386 | 0.206 | 0.134 | 0.097 | 0.075 | 0.060 | 0.050 | 0.042 | 0.037 | 0.032 | 0.029 | 0.026 | 0.023 | 0.021 | 0.020 | 0.018 | 0.017 | 0.016 | 0.015 | 0.014 |
| 15 | 0.423 | 0.233 | 0.153 | 0.111 | 0.086 | 0.069 | 0.058 | 0.049 | 0.043 | 0.037 | 0.033 | 0.030 | 0.027 | 0.025 | 0.023 | 0.021 | 0.019 | 0.018 | 0.017 | 0.016 |
| 16 | 0.457 | 0.258 | 0.172 | 0.126 | 0.098 | 0.079 | 0.066 | 0.056 | 0.049 | 0.043 | 0.038 | 0.034 | 0.031 | 0.028 | 0.026 | 0.024 | 0.022 | 0.021 | 0.019 | 0.018 |
| 17 | 0.488 | 0.283 | 0.190 | 0.140 | 0.109 | 0.089 | 0.074 | 0.063 | 0.055 | 0.048 | 0.043 | 0.039 | 0.035 | 0.032 | 0.029 | 0.027 | 0.025 | 0.023 | 0.022 | 0.020 |
| 18 | 0.516 | 0.306 | 0.208 | 0.154 | 0.120 | 0.098 | 0.082 | 0.070 | 0.061 | 0.054 | 0.048 | 0.043 | 0.039 | 0.036 | 0.033 | 0.030 | 0.028 | 0.026 | 0.024 | 0.023 |
| 19 | 0.540 | 0.327 | 0.224 | 0.167 | 0.131 | 0.107 | 0.089 | 0.076 | 0.066 | 0.059 | 0.052 | 0.047 | 0.043 | 0.039 | 0.036 | 0.033 | 0.031 | 0.029 | 0.027 | 0.025 |
| 20 | 0.560 | 0.345 | 0.239 | 0.179 | 0.141 | 0.115 | 0.096 | 0.082 | 0.072 | 0.063 | 0.056 | 0.051 | 0.046 | 0.042 | 0.039 | 0.036 | 0.033 | 0.031 | 0.029 | 0.027 |
| 21 | 0.577 | 0.360 | 0.251 | 0.189 | 0.149 | 0.122 | 0.102 | 0.088 | 0.076 | 0.067 | 0.060 | 0.054 | 0.049 | 0.045 | 0.041 | 0.038 | 0.035 | 0.033 | 0.031 | 0.029 |
| 22 | 0.590 | 0.373 | 0.261 | 0.197 | 0.156 | 0.128 | 0.107 | 0.092 | 0.080 | 0.071 | 0.063 | 0.057 | 0.052 | 0.047 | 0.043 | 0.040 | 0.037 | 0.035 | 0.033 | 0.031 |
| 23 | 0.599 | 0.382 | 0.269 | 0.203 | 0.161 | 0.132 | 0.111 | 0.095 | 0.083 | 0.073 | 0.066 | 0.059 | 0.054 | 0.049 | 0.045 | 0.042 | 0.039 | 0.036 | 0.034 | 0.032 |
| 24 | 0.605 | 0.387 | 0.274 | 0.207 | 0.164 | 0.135 | 0.113 | 0.097 | 0.085 | 0.075 | 0.067 | 0.060 | 0.055 | 0.050 | 0.046 | 0.043 | 0.040 | 0.037 | 0.035 | 0.032 |
| 25 | 0.607 | 0.390 | 0.276 | 0.209 | 0.166 | 0.136 | 0.115 | 0.098 | 0.086 | 0.076 | 0.068 | 0.061 | 0.055 | 0.051 | 0.047 | 0.043 | 0.040 | 0.037 | 0.035 | 0.033 |
| 26 | 0.607 | 0.389 | 0.275 | 0.208 | 0.165 | 0.136 | 0.114 | 0.098 | 0.086 | 0.076 | 0.068 | 0.061 | 0.055 | 0.051 | 0.046 | 0.043 | 0.040 | 0.037 | 0.035 | 0.033 |
| 27 | 0.602 | 0.385 | 0.272 | 0.205 | 0.163 | 0.133 | 0.112 | 0.096 | 0.084 | 0.074 | 0.066 | 0.060 | 0.054 | 0.050 | 0.046 | 0.042 | 0.039 | 0.037 | 0.034 | 0.032 |
| 28 | 0.594 | 0.377 | 0.265 | 0.200 | 0.158 | 0.130 | 0.109 | 0.094 | 0.082 | 0.072 | 0.064 | 0.058 | 0.053 | 0.048 | 0.044 | 0.041 | 0.038 | 0.035 | 0.033 | 0.031 |
| 29 | 0.583 | 0.366 | 0.256 | 0.193 | 0.152 | 0.125 | 0.105 | 0.090 | 0.078 | 0.069 | 0.062 | 0.056 | 0.050 | 0.046 | 0.042 | 0.039 | 0.036 | 0.034 | 0.032 | 0.030 |
| 30 | 0.568 | 0.352 | 0.245 | 0.183 | 0.144 | 0.118 | 0.099 | 0.085 | 0.074 | 0.065 | 0.058 | 0.052 | 0.048 | 0.043 | 0.040 | 0.037 | 0.034 | 0.032 | 0.030 | 0.028 |

Figure 4.27: Model output for *Crash* Probability.

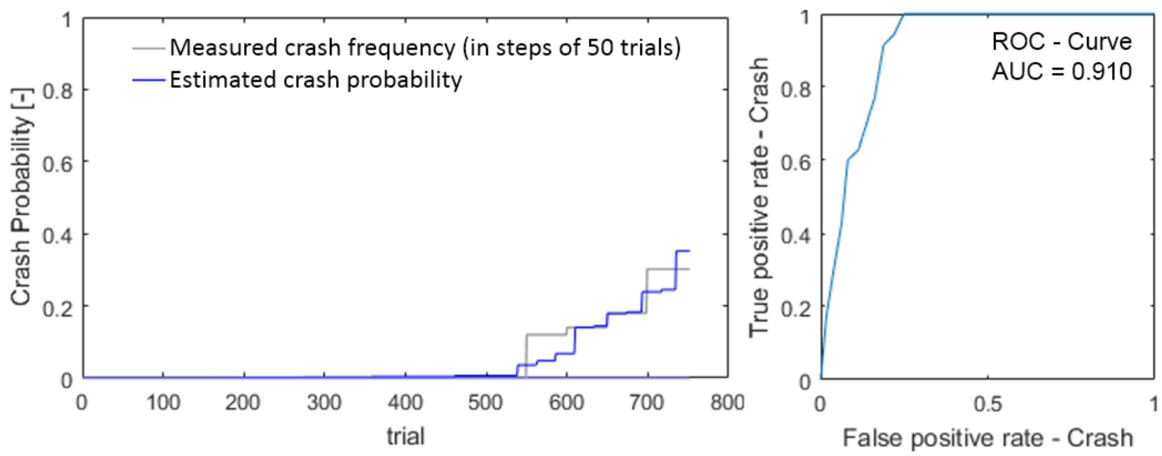



Figure 4.28: Left: Estimation and measures of *Crash* Probability, ordered by estimated *Crash* Probability. Crash frequency of measures is represented by the mean crash occurrence of 50 take-over situations each. Right: Receiver Operator Characteristics Curve for the *Crash* Probability model.

## 4.5 Model Improvements

The proposed models show restrictions, for example regarding the consideration of outliers or deviations of residuals from the normal distribution. In the following, possibilities of facing these limitations are introduced and adapted to the models' requirements.

### 4.5.1 Handling Outliers

Outliers in the data-set influence the $\beta$-estimation and lead to biased OLS predictions. This can be prevented by excluding outliers (Subsection 4.5.1.1) or using algorithms that are more robust to outliers than OLS (Subsection 4.5.1.2).

#### 4.5.1.1 Excluding Crashes from Regression

One major source for outliers in the data-set are situations leading to a collision, as behavior differs in crash and near-crash situations. Additionally, crashes with vehicles in the neighboring lane lead to a TTC of zero, and those values are treated equally to TTC values measuring time distance to the obstacle ahead.

Out of 753 take-over situations, 35 crashes occurred. Although excluding those crashes is reasonable, this only leads to minor changes in the models as listed in Table 4.11. A division into crash and no-crash models therefore appears disproportionate.

Table 4.11: Model quality with and without(*) crash-situations.

| Variable | $\overline{R}^2$ | $\overline{R}^2*$ | $RMSE$ | $RMSE^*$ | $N_{Cook}$ | $N_{Cook}*$ |
|---|---|---|---|---|---|---|
| *GazeReactionTime* | .109 | .107 | 0.11 | 0.11 | 27 | 27 |
| *Take-OverTime* | .347 | .316 | 0.87 | 0.82 | 69 | 64 |
| *Lat.Acc.* | .199 | .197 | 1.49 | 1.38 | 67 | 64 |
| *Long.Acc.* | .345 | .352 | 3.53 | 3.51 | 52 | 50 |
| *TTC* | .509 | .484 | 1.08 | 1.08 | 65 | 62 |

* Regression without crash-samples. $N_{Cook}$ is the number of values of Cook's Distance D that are larger than 3 times the mean of all D.

#### 4.5.1.2 Robust Regression

As outliers may contain the most interesting sample information (Belsley et al., 1980; Montgomery & Peck, 1992), they are kept in the regression. In order not to distort the model by considering outliers, robust regression methods can be applied, which are more resilient regarding outliers and violation of heteroscedasticity than OLS. In robust regression, weight functions are applied to the errors, usually reducing the magnitude of large residuals. There are several different robust regression weight functions, and eight of the most common were applied to the regression models. Figure 4.29 shows the effect of the robust regression weight functions on the models' performance.

| | None | | Andrews | | Bisquare | | Cauchy | | Fair | | Huber | | Logistic | | Talwar | | Welsch | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | RMSE | $R^2$ | RMSE | $R^2$ | RMSE | $R^2$ | RMSE | $R^2$ | RMSE | $R^2$ | RMSE | $R^2$ | RMSE | $R^2$ | RMSE | $R^2$ | RMSE | $R^2$ |
| *ReactionTime* | 0.107 | 0.109 | 0.099 | 0.145 | 0.099 | 0.144 | 0.100 | 0.143 | 0.101 | 0.149 | 0.099 | 0.133 | 0.100 | 0.143 | 0.096 | 0.129 | 0.100 | 0.142 |
| *Take-OverTime* | 0.865 | 0.347 | 0.811 | 0.431 | 0.810 | 0.429 | 0.802 | 0.417 | 0.812 | 0.431 | 0.790 | 0.402 | 0.803 | 0.418 | 0.774 | 0.360 | 0.803 | 0.414 |
| *Lat.Acc.* | 1.490 | 0.199 | 1.139 | 0.230 | 1.143 | 0.230 | 1.182 | 0.244 | 1.231 | 0.264 | 1.186 | 0.229 | 1.201 | 0.249 | 1.050 | 0.224 | 1.158 | 0.234 |
| *Long.Acc.* | 3.533 | 0.345 | 3.746 | 0.398 | 3.747 | 0.398 | 3.755 | 0.423 | 3.514 | 0.482 | 3.837 | 0.381 | 3.736 | 0.434 | 3.533 | 0.345 | 3.758 | 0.406 |
| *TTC* | 1.081 | 0.509 | 1.158 | 0.547 | 1.136 | 0.555 | 1.071 | 0.603 | 1.071 | 0.627 | 1.074 | 0.576 | 1.071 | 0.600 | 1.086 | 0.525 | 1.267 | 0.497 |

Figure 4.29: Comparison of different robust weight functions regarding RMSE and $\overline{R}^2$.

The robust regression leads to an improved performance in almost all models, while the "Fair" weight function (Equation 4.40) shows the best combination of maximizing $\overline{R}^2$ and minimizing the RMSE. This is why it is chosen as the most suitable robust regression method and used for the following optimization of the models.

$$w = \frac{1}{1+|r|} \tag{4.40}$$

### 4.5.2 Handling Non-Normal Distributions

Apart from outliers, OLS estimates $\beta_i$ based on the assumption of a normal distribution of measures. Distinct skewness leads to a biased prediction and can be addressed by different methods that are described hereafter.

#### 4.5.2.1 Multinomial Logistic Regression

*Long.Acc.* showed large deviations of errors from normal distribution and *Lat.Acc.* also deviated, but to a much smaller extent. To a certain degree, generalized linear models can deal with different distributions (cf. Subsection 4.5.2.2), but *Long.Acc.* is rather bi- or multinomial than distributed around one mean and should be modeled as such. Multinomial regressions are performed for *Long.Acc.* (based on the linearized version of Equation 4.18) and *Lat.Acc.* (based on linearized Equation 4.21), similar to the procedure in Subsection 4.4.7. Therefore, the accelerations are transformed to ordinal scale by assigning them to the three groups of $0 - 3.5\,m/s^2$, $3.5 - 7.0\,m/s^2$ and $> 7\,m/s^2$, representing low, medium and high accelerations.

While modeling, consecutively excluding insignificant parameters with low effect sizes leads to the terms for *Long.Acc.* (Equation 4.44) and *Lat.Acc.* (Equation 4.42), in which $t$ resembles the regression equations of Subsection 4.4.3 and Subsection 4.4.4 with regard to the composition of predictors, with one difference for the longitudinal model, where *TrafficDensity* shows linear instead of exponential influence.

$$\sigma_{lat/long} = \frac{1}{1+e^t} \tag{4.41}$$

$$t_{lat} = \beta_0 + \beta_1 I_{TimeBudget} + \beta_2 I_{Lane} + \beta_3 I_{TrafficDensity} + ...$$
$$... + \beta_4 I^2_{TrafficDensity} + \beta_5 \ln I_{Repetition} + \beta_6 I_{Age} + \beta_7 I^2_{Age} \tag{4.42}$$

$$t_{lat} = \beta_0 + 0.458 * I_{TimeBudget} - 0.386 * I_{Lane} - 0.261 I_{TrafficDensity} + ...$$
$$... + 0.009 * I^2_{TrafficDensity} + 0.695 * \ln I_{Repetition} + 0.101 * I_{Age} - 0.001 * I^2_{Age} \tag{4.43}$$
$$with\ \beta_0 = -3.419\ and\ -1.126$$

$$t_{long} = \beta_0 + \beta_1 I_{TimeBudget} + \beta_2 I_{TrafficDensity} + ...$$
$$... + \beta_3 \ln I_{Repetition} + \beta_5 I_{Age} + \beta_6 I^2_{Age} \tag{4.44}$$

$$t_{long} = \beta_0 + 0.679 * I_{TimeBudget} - 0.062 * I_{TrafficDensity} + ...$$
$$... + 1.031 * \ln I_{Repetition} - 0.125 * I_{Age} + 0.001 * I^2_{Age} \tag{4.45}$$
$$with\ \beta_0 = -2.756\ and\ -2.062$$

To assess the models' accuracy, Figure 4.30 and Figure 4.31 display the estimated probabilities and measured frequencies of accelerations as located in the different acceleration bandwidths. High lateral and medium longitudinal accelerations are both rather rare, which leads to low variance within the model and is represented by a low probability of occurrence. While for some conditions, estimations fit the data, the fit of the model deviates up to approximately 0.2 or 20% in others. The ROC curves (Figure 4.32) show a medium quality of the models, indicating that the logistic regression could not address the majority of variance. Nevertheless, when looking at *Long.Acc.*, the logistic regression has the advantage of predicting values on an individual level, rather than predicting a theoretical mean acceleration that is actually not present in the data, as it is composed of very high and low accelerations. As this is the aim of the model approach, the logistic regression appears to be superior to the OLS regression for modeling *Long.Acc.* in take-over scenarios of HAVs.

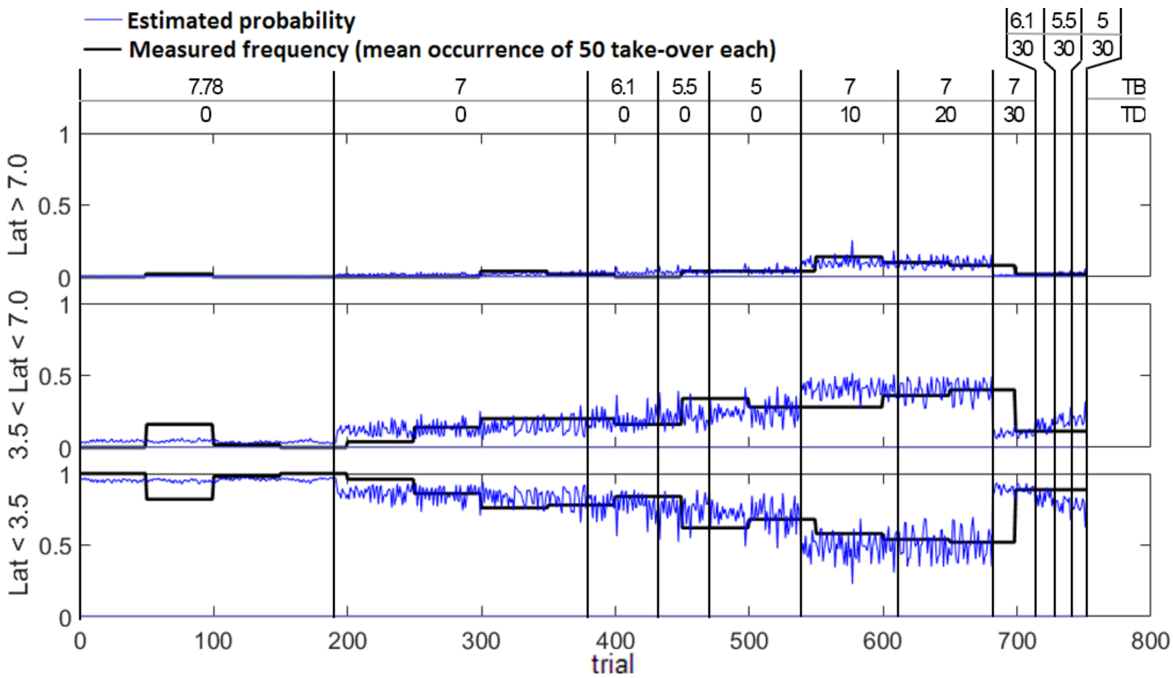



Figure 4.30: Multinomial logistic regression of *Lat.Acc.*

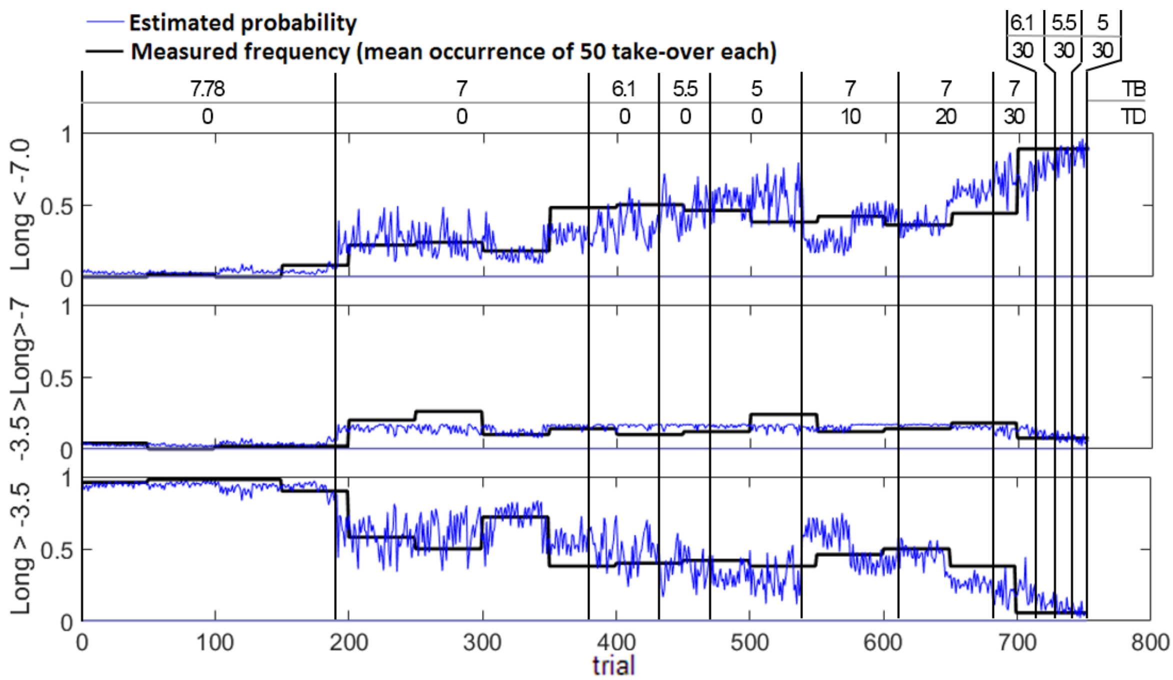



Figure 4.31: Multinomial logistic regression of *Long.Acc.*

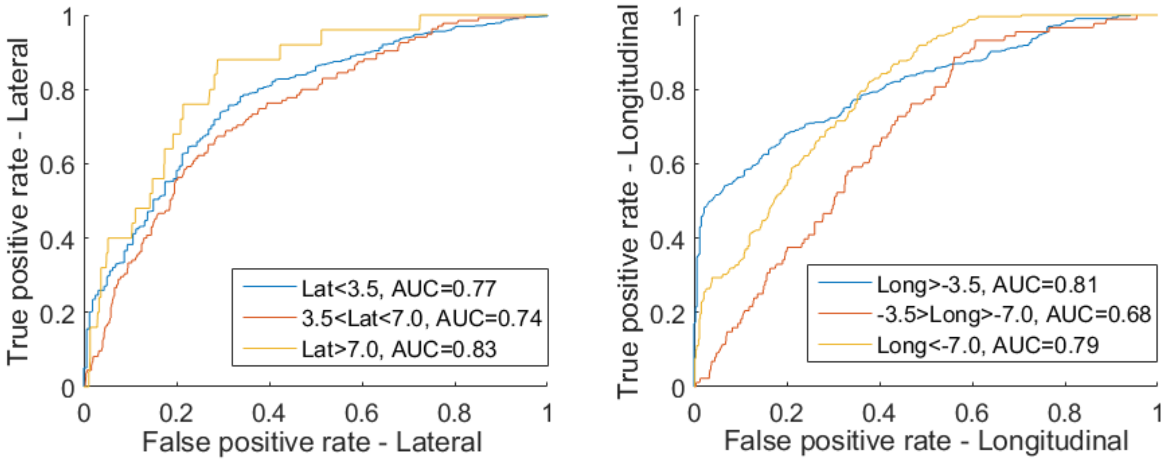



Figure 4.32: ROC-curve for *Lat.Acc.* (left) and *Long.Acc.* (right).

#### 4.5.2.2 Generalized Model

In contrast to OLS, generalized models can consider error distributions that deviate from the normal distribution. In this way, skewness of data can be attributed and adequately considered. Apart from *Long.Acc.*, which is modeled by logistic regression (Subsection 4.5.2.1), especially *Take-OverTime* and *Lat.Acc.* indicate skewed deviations (cf. Section 4.4) and are therefore selected for calculating generalized regressions. Both are characterized by having a minimum size (lower border) and a positive skewness like a gamma distribution. Using gamma for the generalized regression leads to only slight and insignificant changes in the models' characteristics (Table 4.12), supporting the assumption that OLS regression is rather unaffected by the skewness of the measures.

Table 4.12: Model quality with(*) and without Generalized Regression (gamma distribution).

| Variable | $\overline{R}^2$ | $\overline{R}^2$* | $RMSE$ | $RMSE$* |
|---|---|---|---|---|
| *Take-OverTime* | .347 | .368 | 0.87 | 0.85 |
| *Lat.Acc.* | .199 | .193 | 1.49 | 1.49 |

### 4.5.3 Mixed-Effect Models - Driver Induced Variance

It is assumed that a large share of unexplained variance is induced by different strategies and preconditions of the drivers rather than by so-far unconsidered situational parameters. To draw conclusions about the magnitude of driver-induced variance, mixed-effect models are used to calculate the magnitude of a random (driver) predictor $z$ (Equation 4.46) that shifts the prediction function in dependence of the random factor.

$$MixedEffectModel : y = \beta_0 + \beta_1 x_1 + ... + \beta_n x_n + uz + \epsilon \tag{4.46}$$

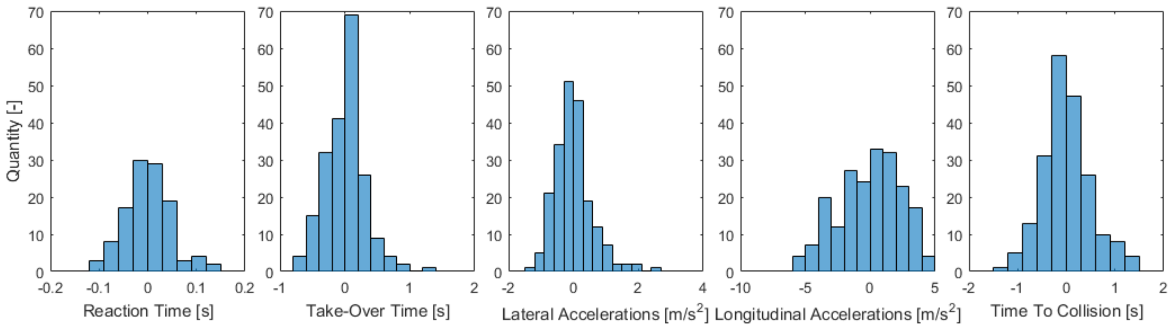



Figure 4.33: Histograms of estimated random effects.

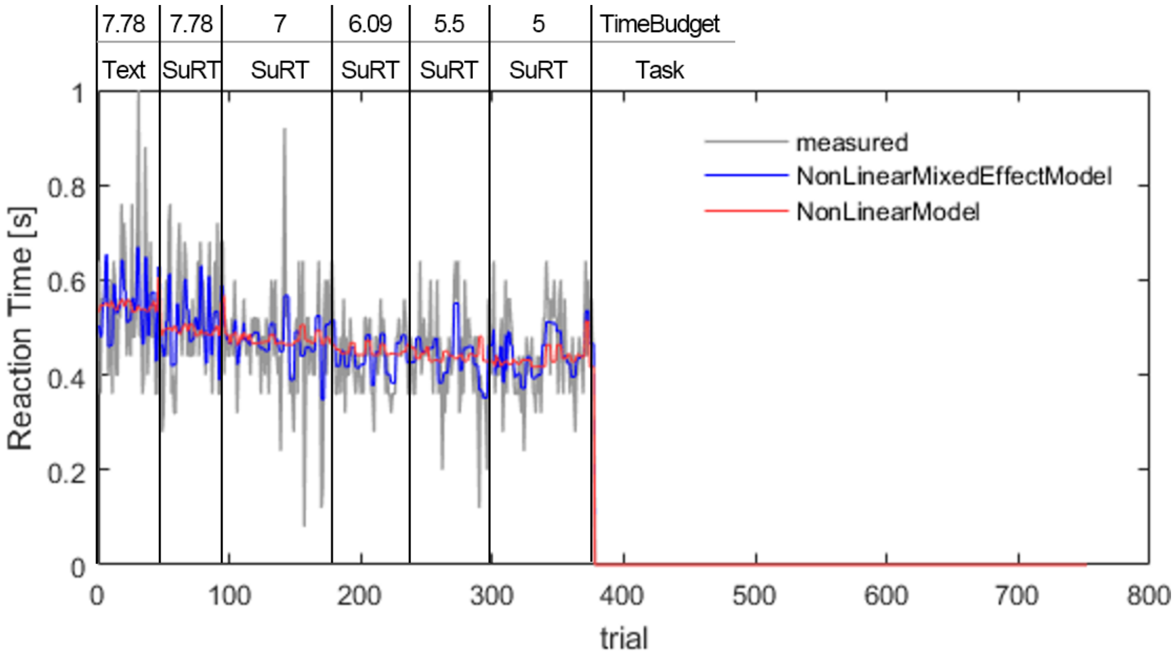



Figure 4.34: Comparison of fit for *GazeReactionTime* of NonLinearModel, and MixedEffectModel.

The current data-set has a three-level structure of 753 take-overs, 203 participants, and on average 3.7 take-overs per participant. To extract the influence of individual drivers, several sampling points for each driver are necessary, which is hardly the case in the current data-set with 3.7 take-overs per participant. Calculating mixed-effect models in this level is therefore limited by the quantity of sampling points and has only low statistical power. On the second level, the source of variance for all drivers, a sample of 203 implies more power (Snijders, 2005). The resulting regression equations of the different models are used for calculating the mixed-effect regressions. Figure 4.33 shows histograms of the estimated random effects induced by the drivers. The narrower those distributions of random effects are, the less influence is attributed to the drivers. Figure 4.34 shows a fit example of the different regression methods for *GazeReactionTime*. The mixed-effect estimation clearly shows more variance and therefore a larger explanation of variance in the data. The remaining plots can be found in Appendix A.

Table 4.13: Model quality with(*) and without random effects.

| Variable | $\overline{R}^2$ | $\overline{R}^2*$ | $RMSE$ | $RMSE^*$ |
|---|---|---|---|---|
| *GazeReactionTime* | .109 | .509 | 0.11 | 0.08 |
| *Take-OverTime* | .347 | .569 | 0.87 | 0.70 |
| *Lat.Acc.* | .199 | .497 | 1.49 | 1.18 |
| *Long.Acc.* | .345 | .736 | 3.53 | 2.25 |
| *TTC* | .509 | .731 | 1.08 | 0.80 |

According to expectations, Table 4.13 shows a significant improvement of $\overline{R}^2$and RMSE when considering the driver as a simple additive random effect and mixed-effect models are able to explain the majority of variance in almost all models, while smaller parts are still unexplained and caused by other random effects or unconsidered predictors. Especially those models that showed less adequacy while modeling (*GazeReactionTime*, *Lat.Acc.*, *Long.Acc.*) benefit most from the mixed-effect estimation and gain between 0.3 and 0.4 in $\overline{R}^2$. On the downside, model output can only be predicted when the random effect of the driver is somehow assessed, for example by driver monitoring and modeling the random effect based on parameters such as vigilance, trust, attention and others. In consequence, *Age* and *Repetition* could be moved to the model estimating drivers' disposition.

### 4.5.4 Variance due to Maneuver Type

Evaluation revealed that much variance within the data is produced by participants braking in the take-over scenarios. Some participants showed prompt but slight braking as a reaction to the TOR, others performed a full-force braking after they arrived at the decision that no evasive maneuver was possible or adequate. This change in maneuver type is also present for individual participants. There is less variance within the situations with no brake application and the evasive maneuvers are of a more similar kind. One way to deal with this variance due to braking is the subdivision of data into groups, based on the occurrence of brake applications. The probability for the occurrence of brake applications can be modeled similar to *Crash* by logistic regression, and different models for the dependent variables could be derived, forming a model tree. The logistic regression for *Brake* leads to a very similar composition of variables as in the regression for *Long.Acc.*, but with *TrafficDensity* considered as linear. Table 4.14 contains the resulting predictors and statistics.

Table 4.14: Coefficient estimates for *Brake*

| Coef. | Expl. Var. | Est. | SE | tStat | p-Value | Pear. r | Cohen's d |
|---|---|---|---|---|---|---|---|
| $\beta_0$ | - | -3.142 | 1.232 | -2.551 | .011 | .093 | -.187 |
| $\beta_1$ | *TimeBudget* | .804 | .148 | 5.418 | <.001 | .195 | .398 |
| $\beta_2$ | *TrafficDensity* | -.049 | .011 | -4.612 | <.001 | .167 | -.339 |
| $\beta_3$ | *Repetition* | 1.115 | .198 | 5.622 | <.001 | .202 | .413 |
| $\beta_4$ | *Age* | -.200 | .043 | -4-665 | <.001 | .169 | -.343 |
| $\beta_5$ | *Age* $^2$ | .002 | .0005 | 4.399 | <.001 | .160 | .323 |

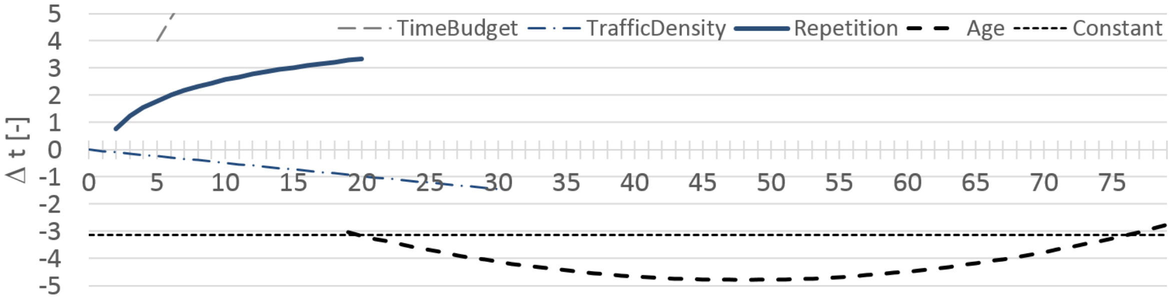



Figure 4.35: Contribution of the different explanatory variables to t for estimating *Brake* Probability.

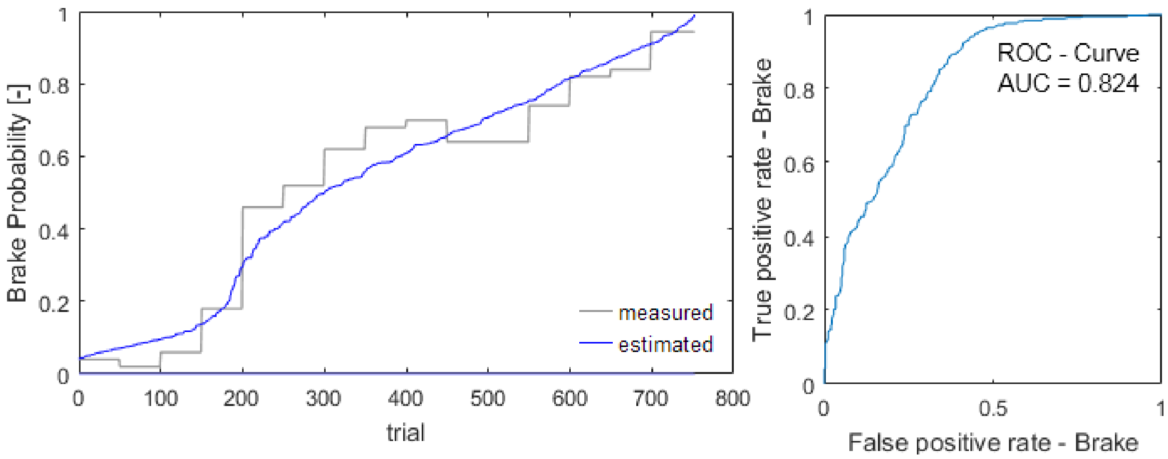



Figure 4.36: Left: Estimation and measures of *Brake* Probability, ordered by estimated *Brake* Probability. Brake frequency of measures is represented by the mean of 50 take-over situations each. Right: Receiver Operator Characteristics Curve for the *Brake* Probability model.

With an AUC of >0.8, the estimation of *Brake* probability seems reasonable. Nevertheless, Subsection 4.5.3 showed a high dependence of *Long.Acc.* on a random effect attributed to the driver. Knowing the drivers' predisposition would therefore likewise improve predictions of the logistic *Brake* model.

In addition to the logistic regression of *Brake*, the other take-over performance metrics are modeled for both sets of situations, those with and without brake application. The procedure is similar to the modeling in Section 4.4 and therefore not described in detail. The data-set is split in situations with brake application and situations where the driver handled the situation without braking. Based on these data-sets, the regression analysis for *Take-OverTime*, *Lat.Acc.*, and *TTC* is conducted under consideration of the robust regression weight function "Fair" (cf. Subsection 4.5.1.2). Furthermore, the logistic regression for *Long.Acc.* is repeated with the data-set that contains the situations with brake application. The final models, including equations and graphs, can be found in Appendix B. Models' fit, measured by the coefficient of determination $\overline{R}^2$ and RMSE, varies compared to the models that consider the whole data-set (cf. Table 4.15).

Table 4.15: Model quality with and without divided data-set.

| Variable | $\overline{R}^2$ | $\overline{R}^2{}_0$ | $\overline{R}^2{}_1$ | $RMSE$ | $RMSE_0$ | $RMSE_1$ |
|---|---|---|---|---|---|---|
| *Take-OverTime* | .431 | .221 | .252 | 0.812 | 0.797 | 0.935 |
| *Lat.Acc.* | .264 | .432 | .164 | 1.231 | 0.989 | 1.518 |
| *TTC* | .627 | .727 | .442 | 1.071 | 0.917 | 1.200 |

$\overline{R}^2{}_0$ / $RMSE_0$: Situations without the occurrence of brake application.
$\overline{R}^2{}_1$ / $RMSE_1$: Situations with the occurrence of brake application.

A reduction in $\overline{R}^2$ can be expected, as much variance in the data is already explained by the logistic brake model and cannot be explained by predictors of the separated regressions. In contrast, the RMSE should decrease, as the prediction should gain accuracy due to the segmentation. Looking at the results, there are only minor changes in the quality of the *Take-OverTime* model. The segmentation based on brake application did not lead to a significant improvement for predicting the *Take-OverTime*. For *Lat.Acc.* and *TTC*, accuracy improves when modeling the non-braking take-overs, but decreases for the braking ones, which meets the expectations.

The quality of the *Long.Acc.* model decreases (AUC1=0.70; AUC2=0.58; AUC3=0.69) which is, similar to less explainable variance in the other regression models, likely to be caused by the substitution of situations with no brake application and thus substitution of explainable variance. The final logistic brake model considers *TimeBudget*, *TrafficDensity*, and *Load*, while higher values for *Load* and *TimeBudget* lead to reduced braking, whereas a higher *TrafficDensity* leads to intensified braking.

## 4.6 Final Modeling Approach

In this thesis, different models have been proposed and improved, leading to a mixed approach for modeling performance in take-over scenarios. It is evident that model quality could be significantly improved by introducing the driver as a predictor (Subsection 4.5.3), as driver strategies play a dominant role with regard to take-over performance. This would imply that the driver-induced variance must be somehow assessed in order to predict the models' output. The mixed-effect models are an important approach, but cannot be further applied in this thesis, as modeling the predisposition of the driver is not part of this thesis.

The resulting combined modeling approach is depicted in Figure 4.37, and the corresponding final regression equations are given below. Linked to the previously introduced take-over procedure (Figure 2.10), the *GazeReactionTime*, and *Take-OverTime* can be derived from $t_{GR}$ and $t_T$ by means of the weighted generalized linear models. These timing aspects could also have been modeled by a modular additive system (Figure 2.14), but without a reliable link to take-over quality. The final model approach addresses the take-over quality by modeling *Long.Acc.*, *Lat.Acc.*, and *TTC* in dependence on the maneuver type (braking vs. no braking) by generalized non-linear models and a multinomial ordinal logistic regression. Additionally, the *Crash* probability is modeled by a nominal logistic regression, completing the characterization and modeling of take-over quality. An impaired take-over performance due to non-driving-related tasks, as suggested by multiple resources and mental-workload theory of Wickens (2008a) or the theory of arousal (Yerkes & Dodson, 1908), does not become apparent in the models with the selected experimental design. While $GazeReactionTime$, $Long.Acc.$, and $TTC$ actually include $Load$ in the regression, tasks considered to use more resources lead to a better take-over quality, as further discussed in Section 4.7. The other fundamental models of human perception and cognition could be affirmed by the experiments and the final model approach. The theory of learning and skill improvement (cf. Figure 2.5) is present in several models, and the assumed logarithmic trend could also be confirmed. In a similar manner, the models meet assumptions derived from the human information processing theory of Wickens et al. (2013) (cf. Figure 2.3). It could be verified that demanding scenarios, for example due to a high traffic density, impair the take-over performance, explainable by limited attention resources of the driver, which are needed for perception, cognition, response selection, and execution. Hereinafter, the final regression equations are stated.

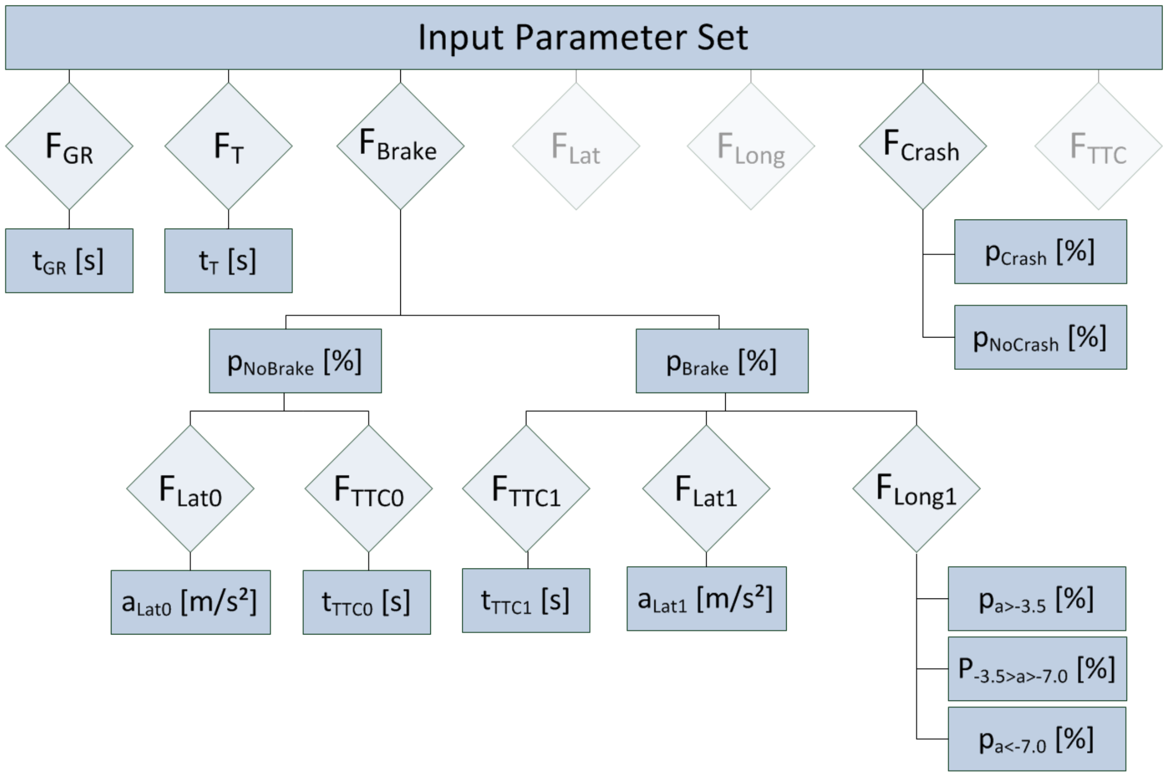



Figure 4.37: Final model tree.

**Final Regression Equations**

- $GazeReactionTime$: Modeled by a generalized non-linear model with the weight function "Fair", considering $TimeBudget$, $Load$, and $Age$. RMSE=0.101; $\overline{R}^2$=0.149.

$$t_R = 0.255 + 0.024 * I_{TimeBudget} + 0.020 * I_{Load} + 2.09 * 10^{-4} * (I_{Age} - 32.254)^2 \tag{4.47}$$

- *Take-OverTime*: Modeled by a generalized non-linear model with the weight function "Fair", considering *TimeBudget*, *Lane*, *TrafficDensity*, *Repetition*, and *Age*. RMSE=0.812; $\overline{R}^2$=0.431.

$$\begin{aligned} t_T = 2.068 + 0.329 * I_{TimeBudget} - 0.147 * (I_{Lane} - 1.936)^2 - ... \\ ... - 0.006 * (I_{TrafficDensity} - 15.667)^2 - 0.571 * \ln I_{Repetition} + ... \\ ... + 2.121 * 10^{-4} * (I_{Age} - 46.235)^2 \end{aligned} \tag{4.48}$$

- *Brake*: Modeled by a nominal logistic regression, predicting probability of brake application, considering *TimeBudget*, *TrafficDensity*, *Repetition*, and *Age* (AUC=0.824).

$$\sigma = \frac{1}{1 + e^t} \tag{4.49}$$

$$\begin{aligned} t_{Brake} = -3.142 + 0.804 * I_{TimeBudget} - 0.049 * I_{TrafficDensity} + ... \\ ... + 1.115 * lnI_{Repetition} - 0.200 * I_{Age} + 0.002 * I_{Age^2} \end{aligned} \tag{4.50}$$

- *Lat.Acc.*: Modeled by two generalized non-linear models with the weight function "Fair", subdivided based on brake application, considering *TimeBudget*, *Lane*, *TrafficDensity*, *Repetition*, and *Age* for non-braking (RMSE=0.989; $\overline{R}^2$=0.432) and *TrafficDensity* and *Age* for braking situations (RMSE=1.518; $\overline{R}^2$=0.164).

$$\begin{aligned} a_{Lat0} = 6.514 - 0.487 * I_{TimeBudget} + 0.343 * I_{Lane} - ... \\ ... - 0.004 * (I_{TrafficDensity} - 17.200)^2 - 0.267 * \ln I_{Repetition} + ... \\ ... + 6.322 * 10^{-4} * (I_{Age} - 47.432)^2 \end{aligned} \tag{4.51}$$

$$\begin{aligned} a_{Lat1} = 3.744 - 0.007 * (I_{TrafficDensity} - 14.769)^2 + ... \\ ... + 4.353 * 10^{-4} * (I_{Age} - 35.306)^2 \end{aligned} \tag{4.52}$$

- *Long.Acc.*: Modeled by a multinomial ordinal logistic regression, predicting probability of accelerations $> -3.5\, m/s^2$ (AUC=0.70), $-3.5 >$ *Long.Acc.* $> -7\, m/s^2$ (AUC=0.58), $< -7.0\, m/s^2$ (AUC=0.69), considering *TimeBudget*, *TrafficDensity*, and *Load*.

$$\begin{aligned} \sigma_{Long} = (1 + e^{\beta_0 + 0.388 * I_{TimeBudget} - 0.049 * I_{TrafficDensity} + 0.438 * I_{Load}})^{-1} \\ with\ \beta_0 = -4.511\ and\ -3.282 \end{aligned} \tag{4.53}$$

- *TTC*: Modeled by two generalized non-linear models with the weight function "Fair", subdivided based on brake application, considering *TimeBudget*, *TrafficDensity*, *Repetition*, and *Load* for non-braking (RMSE=0.917; $\overline{R}^2$=0.727) and *Time-*

*Budget*, *Lane*, *TrafficDensity*, *Repetition*, *Load*, and *Age* for braking (RMSE=1.200; $\overline{R}^2$=0.442) situations.

$$t_{TTC0} = -4.283 + 0.699 * I_{TimeBudget} + 0.0043 * (I_{TrafficDensity} - 17.518)^2 + ... \\ ... + 0.521 * \ln I_{Repetition} + 0.148 * I_{Load} \quad (4.54)$$

$$t_{TTC1} = -3.584 + 0.513 * I_{TimeBudget} - ... \\ ... - 0.082 * (I_{Lane} - 1.314)^2 + 0.0022 * (I_{TrafficDensity} - 26.086)^2 + ... \\ ... + 0.425 * \ln I_{Repetition} + 0.243 * I_{Load} + 0.019 * I_{Age} \quad (4.55)$$

- *Crash*: Modeled by a nominal logistic regression, predicting probability of brake application considering *Lane*, *TrafficDensity*, and *Repetition* (AUC=0.910).

$$\sigma_{Crash} = \frac{1}{1 + e^{4.108 - 0.360 * I_{TrafficDensity} + 0.007 * I^2_{TrafficDensity} + 1.275 * I_{Repetition}}} \quad (4.56)$$

## 4.7 Discussion of Load Modeling

When ordering the different non-driving-related tasks with regard to their expected impairment of take-over performance based on manual and cognitive load, a direct data analysis showed an ascending order of dependent variables, but in an unexpected direction (Figure 4.4). For tasks that are considered to lead to greater loads, *Take-OverTime*, *Lat.Acc.*, and *Long.Acc.* decrease, and *TTC* increases, indicating an improved performance for the tasks assumed to be highly loading. When modeling *TTC* (Figure 4.23, Equation 4.54 and Equation 4.55), *Load* became significant and showed the same unexpected behavior. Although not reported in the thesis, different ways of re-arranging the non-driving-related task were tested. None of them showed improved results, emphasizing that the proposed order is the best solution for a linear order of the tasks considered with regard to the modeling approach. There are several possible explanations. The effect of the non-driving-related task only has minor effects on the take-over performance in the selected experimental setting (Gold, Berisha, & Bengler, 2015), and quite different tasks showed similar results (Radlmayr et al., 2014). This may change when longer automated drives are considered or new non-driving-related tasks introduced. Furthermore, correlations of *Load*, for example with *Repetition*, could have led to a biased recording of data. Likewise, the influence of *Load* may differ when considering additional data recorded in a different experimental setup. Furthermore, an overcompensation of the task impairment by the driver may be present. In any case, the influence of *Load* on take-over performance was of small magnitude in the reported experiments and did not play a major role when modeling take-over performance.

# 5 Validation

The proposed models were shown to fit the data and predict take-over performance within certain limits. Nevertheless, overfitting (Figure 4.1) or limited permutation of independent variables could lead to poor model performance, which can only be detected by validating the model with new data. The data-set is usually divided into training and validation / test data. This leads to a reduced training data-set and thus to reduced model accuracy, as the estimation is based on fewer values. Furthermore, the method of data splitting is called into question and was found to provide only little incremental information regarding the assessment of validity (Kozak & Kozak, 2003). To avoid this, a new experiment was conducted and additional data was recorded.[1] This is “the most effective method of validating a regression model with respect to its prediction performance” (Montgomery & Peck, 1992, p. 375). The validation data-set should represent the training data regarding its composition (Kozak & Kozak, 2003). As this could not be completely achieved with a single experiment, the model is further compared to take-over experiments of other authors (Section 5.3). This also addresses validity aspects that arise from possible restrictions due to the experimental design and simulator properties. Concerning the validation experiment, it was not possible to vary every dependent variable in it’s full range. Therefore, the variance within the validation data is limited and significantly smaller than in the training data. The less variance is generated by parameter variation, the smaller is the proportion of the variance explained by the model. Comparing coefficients that are related to variance, such as the AUC and $\overline{R}^2$, is therefore not meaningful and leads to biased or wrong evaluations.

## 5.1 Experimental Design and Validation Parametrization

The additional data was recorded in the fix-based driving simulator of the Institute of Ergonomics, similar to Experiment 4, 5, and 6 (Chapter 3). Literature suggests a number of at least 100 test cases (Harrell, 2001). Other sources provide lower numbers of 15 to 20 cases (Montgomery & Peck, 1992). For the validation, 120 take-overs of 30 different participants were recorded.

The parametrization of the validation experiment was governed by different objectives that do not correlate with the modeling approach in this thesis. In this way, the experiment was expected to be comparable with former experiments, which leads to a selection of parameters which is more than sufficient, but not ideal for the models’ validation, as not all combinations could be tested.

- *TimeBudget*: Was set to 6 seconds, a value only represented as a combination of a TB of 5 seconds and a strong automated brake application.

[1] The validation experiment was conducted with the assistance of Anna Feldhütter as part of her Master thesis (Feldhütter, 2015).

- *TrafficDensity*: Was varied between 0 and 10 vehicles per kilometer.
- *Load*: For the majority of take-overs, the SuRT task was applied as a non-driving-related task. Furthermore, half of the participants experienced the take-over with no prior task activity.
- *Age*: Was set to 20 to 30 years.
- *Lane*: Was varied between left, center, and right lane.
- *Repetition*: Each participant experienced one take-over in the familiarization and four take-overs in the experimental condition. As there was an additional take-over, not relevant for validation, repetition varied between 2 and 6.

Parameters were selected in order to obtain both situations with and without brake application. The experiment included five different take-over scenarios, out of which one was not used for validation. The other four scenarios were take-overs with a traffic density of 0 vehicles/km in the right, center, and left lane, and one situation with a traffic density of 10 vehicles/km in the left lane. The order of the situations was randomized, except for the scenarios with a traffic density of 0 vehicles/km in the left lane, which was always the last scenario for examining a different research question. According to the previous experiments, the system limit was represented by a stationary lead vehicle in the current lane on a straight section of the course and with the known audio-visual TOR.

## 5.2 Results Validation Experiment

Three trials had to be excluded, as participants looked up from the SuRT occasionally just before the TOR. In another situation, technical problems led to the exclusion of a fourth take-over. The remaining 116 situations were used for the validation, including 28 situations with a traffic density of 10 vehicles/km. In 101 of the 116 situations, the SuRT was implemented, and in the remaining 15 situations there was no non-driving-related task. Participants had a mean age of 24.4 years (SD = 2.4).

Altogether, nine models have to be validated (cf. Figure 4.37). Therefore, the RMSE is calculated based on the validation data (The robust weight function was not considered for estimating the RMSE) and mean values, Standard Deviation (SD), and the proportion of measures within the predicted confidence interval are estimated for drivers in the $TrafficDensity = 0$ and $TrafficDensity = 10$ condition, respectively. To estimate $Lat.Acc.$ and $Long.Acc.$ in dependence on brake applications, the data has to be further subdivided, leading to reduced numbers of trials in some cases (e.g. n=8 non-braking drivers in the $TrafficDensity = 10$ condition).

Table 5.1 summarizes the results of the validation experiment. The SD of the models' predictions is derived from the confidence intervals, as predicted by the models. Equation 5.1 shows the mathematical relationship between the SD and the upper 0.95 confidence interval. To enable this transformation, a normal distribution of errors was assumed.

Table 5.1: Model fit for validation data.

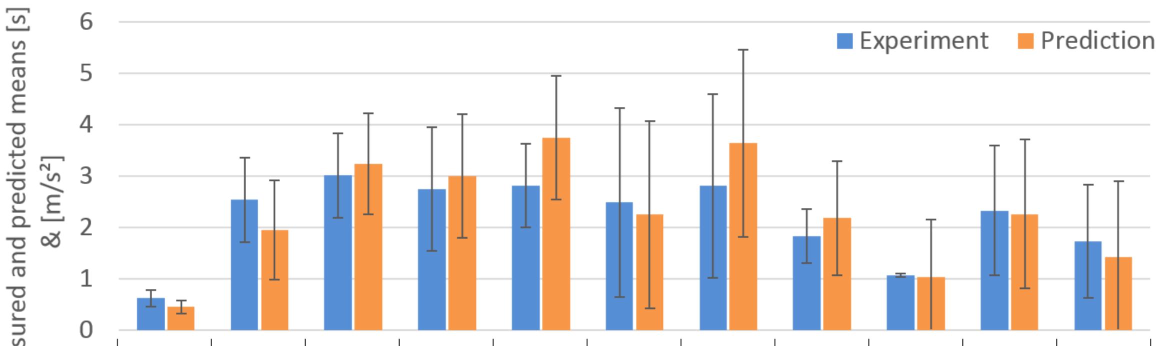
| Model | TD | n | $RMSE$ $Train.$ | $RMSE$ $Validat.$ | $m$ $Exp.$ | $m$ $Pred.$ | $SD$ $Exp.$ | $SD$ $Pred.$ | $Within$ $Ci_{95}$ |
|---|---|---|---|---|---|---|---|---|---|
| $F_{GR}$ | 0/10 | 101 | 0.233 | 0.107 | 0.62 | 0.45 | 0.16 | 0.12 | 69% |
| $F_{T}$ | 0 | 88 | 0.767 | 0.860 | 2.54 | 1.95 | 0.82 | 0.97 | 94% |
| $F_{T}$ | 10 | 28 | 0.767 | 0.860 | 3.01 | 3.24 | 0.82 | 0.98 | |
| $F_{Brake}$ | 0 | 88 | - | - | 42.0% | 61.7% | - | - | - |
| $F_{Brake}$ | 10 | 28 | - | - | 71.4% | 76.8% | - | - | - |
| $F_{Crash}$ | 0 | 88 | - | - | 2.3% | 0.4% | - | - | - |
| $F_{Crash}$ | 10 | 28 | - | - | 7.1% | 7.6% | - | - | - |
| $F_{Lat0}$ | 0 | 51 | 1.188 | 1.209 | 2.75 | 3.00 | 1.21 | 1.20 | 97% |
| $F_{Lat0}$ | 10 | 8 | 1.188 | 1.209 | 2.82 | 3.75 | 0.81 | 1.21 | |
| $F_{Lat1}$ | 0 | 37 | 1.934 | 1.674 | 2.49 | 2.25 | 1.84 | 1.82 | 91% |
| $F_{Lat1}$ | 10 | 20 | 1.934 | 1.674 | 2.81 | 3.64 | 1.79 | 1.83 | |
| $F_{TTC0}$ | 0 | 51 | 0.549 | 0.906 | 1.83 | 2.18 | 0.53 | 1.11 | 100% |
| $F_{TTC0}$ | 10 | 8 | 0.549 | 0.906 | 1.07 | 1.03 | 0.04 | 1.12 | |
| $F_{TTC1}$ | 0 | 37 | 1.190 | 1.182 | 2.33 | 2.26 | 1.27 | 1.45 | 97% |
| $F_{TTC1}$ | 10 | 20 | 1.190 | 1.182 | 1.73 | 1.43 | 1.10 | 1.47 | |
| $F_{Long-low}$ | 0 | 37 | - | - | 14% | 19% | - | - | - |
| $F_{Long-med}$ | 0 | 37 | - | - | 16% | 25% | - | - | - |
| $F_{Long-high}$ | 0 | 37 | - | - | 70% | 56% | - | - | - |
| $F_{Long-low}$ | 10 | 20 | - | - | 0% | 14% | - | - | - |
| $F_{Long-med}$ | 10 | 20 | - | - | 15% | 22% | - | - | - |
| $F_{Long-high}$ | 10 | 20 | - | - | 85% | 64% | - | - | - |

$Exp.$ = Data from validation experiment; $Pred.$ = Models' prediction.

$$SD = \frac{Ci_{95} - \overline{m}}{x} \tag{5.1}$$

$$while: x = percentile_{95} = 1.645 \tag{5.2}$$

The model shows slight deviations regarding *GazeReactionTime*, *Take-OverTime* (TD=0), *Lat.Acc.* (TD=10), and *Brake* (TD=0). In the experiment, *GazeReactionTime* (0.62 s) appeared to be approximately 0.15 seconds longer than predicted (0.45 s) and only 69% of the *GazeReactionTime* values are located within the confidence interval. However, this accuracy is still considered sufficient for predicting gaze reactions in HAVs. In the no-traffic condition, 42% braked as a reaction to the TOR, while the model predicted 62% brake applications. *Brake* was introduced to segment the data and calculate *Lat.Acc.* and *TTC* separately for braking and non-braking drivers. Although the deviation between prediction and measures is obvious and reveals a deficiency of the *Brake* model, it has a minor influence on the prediction of *Lat.Acc.* and *TTC*, as those are rather similar for braking and non-braking drivers. The *Take-OverTime* shows a deviation of 0.59 seconds in the no-traffic condition, while the RMSE is of the same magnitude. This indicates an offset in the validation experiment with higher values throughout, compared to the




| Model: | $F_{GR}$ | $F_T$ | $F_T$ | $F_{Lat0}$ | $F_{Lat0}$ | $F_{Lat1}$ | $F_{Lat1}$ | $F_{TTC0}$ | $F_{TTC0}$ | $F_{TTC1}$ | $F_{TTC1}$ |
|---|---|---|---|---|---|---|---|---|---|---|---|
| TD: | 0 & 10 | 0 | 10 | 0 | 10 | 0 | 10 | 0 | 10 | 0 | 10 |
| n: | 101 | 88 | 28 | 51 | 8 | 37 | 20 | 51 | 8 | 37 | 20 |
| T-Test: | **<0.001** | **<0.001** | 0.328 | 0.297 | 0.092 | 0.574 | 0.155 | **0.045** | 0.921 | 0.826 | 0.469 |

Figure 5.1: Measured and predicted means and standard deviations for *GazeReaction-Time*, *Lat.Acc.* and *TTC*. Indices of the models correspond to Figure 4.37.

model. This could either be an artifact, e.g. due to a different instruction [2], or a hint of an inaccurate model. Nevertheless, 94% of data are located within the 0.95 confidence interval of the model. In the condition with a traffic density of 10, lateral accelerations are predicted higher for both braking and non-braking drivers (3.75/3.36 $m/s^2$) than actually measured (2.82/2.81 $m/s^2$). Considering the small number of cases on the one hand and a good conformity of RMSE and fit of data within the confidence interval on the other, validity can neither be refused nor confirmed. While the model for longitudinal acceleration expectably shows moderate prediction accuracy, all other models are very accurate based on the validation data. Especially *Crash*, *Lat.Acc.* (TD=0), and *TTC* showed good prediction based on a high number of cases. Thus, almost all *TTC* values are located within the confidence intervals of the model (97% to 100%). *Take-OverTime* (TD=10) and *Brake* (TD=10) also performed precisely, although only a smaller amount of data was used for validation.

## 5.3 Comparisons with Other Experiments

If a detailed reporting is provided, results of experiments by other authors can be compared to the models' predictions, and these external data can therefore be used for validation. As a requirement, the explanatory variables in the experiments need to be known and experimental conditions such as the the TOR / HMI and the take-over scenario should be at least similar. The experiments described below fulfill these requirements, and the authors reported all information needed to model the experimental output by the use of the proposed models. Data on a participant-based level is not accessible by extracting information from scientific papers. Nevertheless, means and standard

[2] Participants in the validation study read newspaper articles and watched a video explaining and advertising highly automated vehicles, which might have influenced trust in automated vehicles and thus the take-over time.

deviations can be derived. The validation can be carried out by comparing predictions of mean values, SDs and frequencies with figures reported in the publications.

### 5.3.1 Comparison to Lorenz, Kerschbaum, and Schumann 2014

The first validation is carried out using the experiment of Lorenz et al. (2014), who compared different HMI concepts for HAVs. Forty-three valid take-overs were recorded in the BMW AG dynamic driving simulator. The participants experienced one TOR in a familiarization drive and another TOR in the experiment, which was used for validation and included a TB of seven seconds. The system limit was similar to, for example, scenario 2 in Figure 3.3, with a stranded vehicle in the participants' lane. All parameters needed for the modeling can be retrieved from the paper. The data on the participants' age, reported as mean (31.7 years) and standard deviation (10.1 years), served to generate a normal distribution, reproducing distributed age data for the modeling. The different HMI concepts, which showed significant differences in the experiment, could not be considered in the model and are neglected for the validation. The *Repetition* was set to 2, as participants experienced one take-over during the familiarization.

*GazeReactionTime*, *Take-OverTime*, *Brake*, and *Lat.Acc.* can be compared regarding measured and predicted means, while *GazeReactionTime* and *Take-OverTime* can be modeled under consideration of the whole data-set, and *Lat.Acc.* is calculated by averaging the models for braking and non-braking drivers under consideration of the braking ratio reported in the paper.

- *GazeReactionTime* is modeled by Equation 4.47 with a mean of 0.48 seconds (SD=0.12) and measured to be 0.53 seconds (SD=n.a.)
- *Brake* is modeled by Equation 4.50 with a mean probability of 32% and measured to be 58%
- *Crash*: No crashes occurred in the experiment, in line with the expected low crash probability of 0.7% (Equation 4.56).
- *Lat.Acc.* is modeled by Equation 4.51 and Equation 4.52 with a mean of 2.25 $m/s^2$ (SD=1.55) and measured to be 2.82 $m/s^2$ (SD=1.63)
- *Take-OverTime* is modeled by Equation 4.48 with a mean of 2.54 seconds (SD=0.98) and measured to be 2.92 seconds (SD=0.87)

*GazeReactionTime*, *Take-OverTime*, and *Crash* provide very good predictions of the measured values, for mean as well as standard deviations. *Long.Acc.* and *Lat.Acc.* deviate to a slightly larger extent, but under considerations of higher errors during the modeling process still provide an adequate fit. Overall, the experiment of Lorenz et al. (2014) supports the assumption of validity for the tested models, while the model of *Brake* proved to be more inaccurate.

### 5.3.2 Comparison to Zeeb, Buchner, and Schrauf 2015

The experiment of Zeeb and colleagues (Zeeb et al., 2015) also matches the requirements for consideration as validation data. They conducted a simulator experiment in the dynamic driving simulator of Daimler AG and compared different types of drivers, which are merged for validation. Among other data, they report road fixation time, brake reaction time, and crash probability, which can be modeled by *GazeReactionTime*, *Take-OverTime*, and *Crash*. The data-set includes 89 take-overs. In 80 of these, participants braked as a response to the TOR. In 53 take-overs, drivers were visually distracted, which is why these situations can be considered for validating *GazeReactionTime*. The participants' age varied between 20 and 72 years, similar to the training data, with a mean of 41.8 years (SD=12.6). Again, this information was used to generate normally distributed age data to provide adequate model input. The take-over scenarios are very similar to Experiment 1 (Subsection 3.3.1) with a lead vehicle swerving into the neighboring lane and thus revealing a stranded vehicle ahead with the TOR being announced simultaneously. The neighboring lane was blocked by traffic with an approximate density of 30 vehicles/km (extracted from Figure 3, p. 216). At the moment of the take-over, participants were distracted by a task similar to the Text task ($Load = 4$). The automated system also featured an automated brake application of 2.5 $m/s^2$ together with the TOR, leading to a group specific total *TimeBudget* of 4.15 seconds, 4.65 seconds, and 5.15 seconds, respectively. The participants experienced two take-over situations previously to the measured take-over. *Repetition* was also set to 3 for the modeling. Altogether, the take-overs seem to be recorded in a more critical setup than situations in the training data, as they include and combine very short TBs with very high traffic densities.

- *GazeReactionTime*: Gaze behavior was recorded, and the time to road-fixation value of the 53 visually distracted drivers was measured to be 0.69 seconds (SD=0.20). The road fixation measure differs from *GazeReactionTime*, as *GazeReactionTime* refers to the first gaze directed away from the non-driving-related task after the TOR, whereas road fixations also include road-fixation time, which varies between 150 and 300 ms in take-over scenarios (Kerschbaum et al., 2015, 2014; Gold, Dambock, et al., 2013; Damböck, 2013). In line with these findings, the predicted duration of the *GazeReactionTime* model (Equation 4.47) is 190 ms shorter (0.50 s) with a comparable SD of 0.13, indicating that the *GazeReactionTime* model can also be used to model road fixations by adding an offset of approximately 200 ms.
- *Brake*: Nine participants did not brake as a reaction to the TOR and have been excluded from the evaluation by the authors. The reported values therefore only include data of braking drivers. Nevertheless, this information indicates a brake probability of 89.9%. The model for *Brake* predicts (Equation 4.50) an 8% higher probability of 97.8%.
- *Crash*: Out of the 89 participants, 25 (28.1%) collided with the obstacle or vehicles in the neighboring lane, while the *Crash* model (Equation 4.56) predicts 22 collisions (24.5%).
- *Take-OverTime*: The authors also reported brake reaction times of the 80 participants who braked, under consideration of a similar threshold (10% braking

pedal position). These brake reactions can be modeled by the *Take-OverTime* model (Equation 4.48). The model predicts brake reaction times of 1.75 seconds (SD=0.98), while Zeeb and colleagues measured 1.88 seconds (SD=0.55).

Validation of the models *Brake*, *Crash*, *GazeReactionTime*, and *Take-OverTime* showed accurate prediction capabilities regarding this study. Results further emphasize the validity of the models involved, especially when considering that the authors are not associated with the author of this thesis, driving simulator as well as method are likely to differ, and the scenario was more critical than scenarios considered in the training data-set.

### 5.3.3 Comparison to Kerschbaum, Lorenz and Bengler 2015

The study of Kerschbaum et al. (2015) compared a transformable steering wheel for HAVs to a conventional steering concept. In a within-subject design, participants experienced three take-over situations with each concept. While the different concepts cannot be considered in the model, the other criteria meet the requirements, and the experiment can be used for further validation of the models by averaging the dependent measures regardless of the steering wheel concepts. In contrast to the situations in the training data, two out of three situations took place in a bend instead of on a straight road section, possibly extending the area of validity if the data matches the models' predictions. The system limit was, similar to other experiments, represented by a car accident in the ego-vehicle's lane, with a TB of seven seconds. The participants were engaged in the SuRT. For the validation of *GazeReactionTime* 114 take-over situations can be considered, and 270 take-overs are available for the other variables.

The reported data allows for validation of *GazeReactionTime*, *Crash*, *Lat.Acc.*, as well as *Take-OverTime*, whereas no brake frequency (*Brake*) or TTC values (*TTC*) are reported. As the brake ratios are unknown, the *Lat.Acc.* model cannot be divided to predict lateral accelerations for braking and non-braking drivers and the joint *Lat.Acc.* model ($F_{Lat}$; Figure 4.37; Equation 4.23) is used for the prediction instead. The *Long.Acc.* model cannot be validated either, as brake accelerations for each of the take-overs would be necessary, which cannot be derived from the paper, but solely from the raw data, which is not accessible.

- *GazeReactionTime*: Participants in the experiment reacted after 0.42 seconds (SD=0.13) which is accurately predicted by the *GazeReactionTime* model (0.47s, SD=0.12; Equation 4.47).
- *Crash*: No crashes are reported in the publication, which fits the *Crash* model's prediction of a crash probability of 0.25% (Equation 4.56).
- *Take-OverTime*: Very slight deviations are found for the *Take-OverTime*, which are reported with a mean of 2.64 seconds (SD=0.86) and thus 340 ms longer than the model's prediction of 2.30 seconds (SD=0.98; Equation 4.48). For the condition with the transformable steering wheel, participants reacted about 100 ms later, which would explain parts of the small deviation and indicate a very good model fit.

- *Lat.Acc.*: For lateral accelerations, the model (Equation 4.23) predicts accelerations of 2.22 $m/s^2$ (SD=1.48), which matches the reported 2.51 $m/s^2$ (SD=0.80).

All considered models showed very good predictions, further supporting the assumption of validity, even for take-overs in curved road sections.

### 5.3.4 Comparison to Hergeth 2016

Hergeth et al. (2016) compared four different ways of introducing the HAV to participants of a driving simulator study in a fix-based driving simulator of the BMW AG, which was not used for any of the previously mentioned experiments. Each of the 110 participants received a “basic description” of the system and the TOR. Furthermore, one group was provided with additional information on the system limits, another group received additional information on system limits and experienced two take-over scenarios in the familiarization drive, and a third group experienced the two take-overs but without the additional instruction. For comparing this experiment with the model predictions, the groups without the training in taking over vehicle control were merged, and so were the groups with experience in take-over situations. During the experiment and after the familiarization drive, the 110 participants experienced two take-overs in the center lane, with no traffic in the neighboring lanes and with previous engagement in the SuRT. The models’ parameters were adjusted accordingly, while *Repetition* was set to 1/2 for non-experienced drivers and 3/4 for experienced ones, as the latter experienced two take-overs during the familiarization drive. Age distribution was generated based on the specifications in the paper (20-59 years; mean=29.59; SD=6.87).

The data facilitates validation of *Take-OverTime*, *Brake*, *Crash*, and *TTC*. The required data was retrieved from the charts provided with the best possible accuracy. The SDs could not be derived accurately and are therefore not considered for validation. To calculate the *TTC*, values of the models for braking and non-braking drivers were summed up under consideration of the reported braking probability of 78%.

- *Take-OverTime*: Participants took over vehicle control after 2.28 seconds in the experienced and 2.55 seconds in the inexperienced group. Predictions of the *Take-OverTime* model (Equation 4.48) suggest 2.36 seconds for experienced and 2.85 seconds for inexperienced drivers.
- *Brake*: In both groups, approximately 78% of the participants showed brake responses, while the model (Equation 4.50) predicts only 53.2% for experienced, but 72.9% for inexperienced drivers.
- *Crash*: One collision occurred in the group of inexperienced participants (0.9%), matching the model’s (Equation 4.56) predictions of 1.1%. With experience, no collision was reported (0.0%), also in line with the model-based expectations (0.3%).
- *TTC*: Regarding TTC, both groups created equal mean minimum values of 3.28 seconds, while the model’s predictions differ for experienced (3.02 s) and inexperienced (2.62 s) drivers (Equation 4.54 and Equation 4.55).

The consideration of experimental data of Hergeth et al. (2016) confirms the previous findings. *Take-OverTime* and *Crash* show very good predictive characteristics, while *Brake* deviates to a larger extent. The prediction of *TTC* for experienced drivers is accurate, but drivers without take-over training are underestimated by the model. To a greater extend, this is caused by very performant take-overs in the second situation and not by an inappropriate modeling of the first take-over, which was outside the range of the training data. The different instructions regarding the HAV have a significant influence on take-over performance and could not be taken into account completely by the models. This may have led to inaccuracy of an unknown extent.

## 5.4 Interpretation and Summary of Validation

Table 5.2 summarizes the comparison of mean and SD of the model prediction and measures for the different experiments, which were used for validation. The probability of brake application (*Brake*) and the magnitude of braking (*Long.Acc.*) are modeled with a moderate fit. The models for lateral acceleration (*Lat.Acc.*) provide adequate predictions, although rather small parts of variance can be explained by the model. In all considered experiments, predicted means deviated less than 1 $m/s^2$ from the measured values. The mentioned models would significantly improve and explain an additional 30 to 40% of variance (cf. Subsection 4.5.3) if the drivers' predisposition had been available and could have been considered as a predictor. Unless this predisposition can be retrieved from other sources, such as driver monitoring (which would be recommended and subject to further research), or by recording several take-overs of the particular driver, the accuracy of the modeling, especially for brake application and lateral accelerations, remains limited. The take-over time (*Take-OverTime*) could be validated with a large data-set of 729 new take-overs. Standard deviations are predicted precisely, and means show a good fit of 130 to 670 ms in deviation, which is a strong indication of the model's validity, when considering the wide variety of validation data. The time-until-first-gaze reactions (*GazeReactionTime*) were shown to fit with maximum deviations of the mean of less than 200 ms in the additional 326 situations considered, which is regarded as sufficiently precise for evaluating take-overs in HAVs. As a side effect, the *GazeReactionTime* model also predicts the "eyes-on-road-time", as this measure was consistently 200 ms longer than the values predicted by the *GazeReactionTime* model. The surrogate safety measure time-to-collision (*TTC*) showed a high accuracy in most cases, indicating that the model can be assumed valid. Furthermore, the probability of collisions during a take-over (*Crash*) could be predicted with very high precision in 729 take-overs of all tested validation experiments, emphasizing the good model suitability, which was determined while setting up the model. By considering not only the validation experiment conducted for this thesis, but also including several studies of different authors, a huge validation data-set could be assembled, including aspects such as curvy roads, shorter time budgets, other driving simulators, and new non-driving-related tasks. In this way, it can be assumed that the models are valid and an extension of the range of validity is likely to be legitimate.

Table 5.2: Comparison of measured and predicted means, standard deviations and frequencies.

| Experiment | | $Gold\ (TD=0)$ | | $Gold\ (TD=10)$ | | $Lorenz$ | | $Zeeb$ | | $Kerschbaum$ | | $Hergeth.E$ | | $Hergeth.I$ | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Trials | $n$ | 88 | | 28 | | 46 | | $53-89$ | | $114-270$ | | 110 | | 110 | |
| | | $Meas.$ | $Pred.$ | $Meas.$ | $Pred.$ | $Meas.$ | $Pred.$ | $Meas.$ | $Pred.$ | $Meas.$ | $Pred.$ | $Meas.$ | $Pred.$ | $Meas.$ | $Pred.$ |
| $F_R$ | $m$ | 0.63 | 0.45 | 0.59 | 0.45 | 0.53 | 0.48 | ca.0.5 | 0.50 | 0.42 | 0.47 | - | - | - | - |
| ($n$=326) | $\delta m$ | 0.18 | | 0.14 | | 0.05 | | - | | -0.05 | | - | | - | |
| | $SD$ | 0.18 | 0.12 | 0.10 | 0.12 | n.a. | 0.12 | <0.20 | 0.13 | 0.13 | 0.12 | - | - | - | - |
| $F_T$ | $m$ | 2.54 | 1.95 | 3.01 | 3.24 | 2.92 | 2.25 | 1.88 | 1.75 | ca.2.5 | 2.30 | 2.36 | 2.28 | 2.85 | 2.55 |
| ($n$=729) | $\delta m$ | 0.59 | | -0.23 | | 0.67 | | 0.13 | | ca. 0.2 | | 0.08 | | 0.30 | |
| | $SD$ | 0.82 | 0.97 | 0.82 | 0.98 | 0.87 | 0.98 | 0.55 | 0.98 | 0.86 | 0.98 | - | - | - | - |
| $F_{Brake}$ | | 42.0% | 61.7% | 71.4% | 76.8% | 58% | 32% | 89.9% | 97.8% | - | - | 78% | 53.2% | 78% | 72.8% |
| ($n$=738) | $\delta$ | -19.7 | | -5.4 | | 26% | | -7.9% | | 34.8% | | 24.8% | | 5.2 | |
| $F_{Crash}$ | | 2.3% | 0.4% | 7.1% | 7.6% | 0% | 0.7% | 28.1% | 24.5% | 0% | 0.3% | 0.0% | 0.3% | 0.9% | 1.1% |
| ($n$=729) | $\delta$ | 1.9% | | -0.5% | | -0.7% | | 3.6% | | -0.3% | | -0.3% | | -0.2% | |
| $F_{Lat}$ | $m$ | 2.64 | 2.54 | 2.82 | 3.67 | - | - | - | - | 2.51 | 2.22 | - | - | - | - |
| ($n$=386) | $\delta m$ | 0.10 | | -0.85 | | - | | - | | 0.29 | | - | | - | |
| | $SD$ | 1.51 | 1.47 | 1.58 | 1.48 | - | - | - | - | 0.80 | 1.48 | - | - | - | - |
| $F_{Lat0}$ | $m$ | 2.75 | 3.00 | 2.82 | 3.75 | 2.82 | 2.25 | - | - | - | - | - | - | - | - |
| ($n$=70) | $\delta m$ | -0.25 | | -0.93 | | 0.57 | | - | | - | | - | | - | |
| | $SD$ | 1.21 | 1.20 | 0.81 | 1.21 | 1.63 | 1.55 | - | - | - | - | - | - | - | - |
| $F_{Lat1}$ | $m$ | 2.49 | 2.25 | 2.81 | 3.64 | 2.82 | 2.25 | - | - | - | - | - | - | - | - |
| ($n$=89) | $\delta m$ | 0.24 | | -0.83 | | 0.57 | | - | | - | | - | | - | |
| | $SD$ | 1.84 | 1.82 | 1.79 | 1.83 | 1.63 | 1.55 | - | - | - | - | - | - | - | - |
| $F_{TTC0}$ | $m$ | 1.83 | 2.18 | 1.07 | 1.03 | - | - | - | - | - | - | 3.28 | 3.02 | 3.28 | 2.62 |
| ($n$=99) | $\delta m$ | -0.35 | | 0.04 | | - | | - | | - | | 0.26 | | 0.66 | |
| | $SD$ | 0.53 | 1.11 | 0.04 | 1.12 | - | - | - | - | - | - | - | - | - | - |
| $F_{TTC1}$ | $m$ | 2.33 | 2.26 | 1.73 | 1.43 | - | - | - | - | - | - | 3.28 | 3.02 | 3.28 | 2.62 |
| ($n$=237) | $\delta m$ | 0.07 | | 0.30 | | - | | - | | - | | 0.26 | | 0.66 | |
| | $SD$ | 1.27 | 1.45 | 1.10 | 1.47 | - | - | - | - | - | - | - | - | - | - |
| $F_{Long_{low}}$ | | 14% | 19% | 0% | 14% | - | - | - | - | - | - | - | - | - | - |
| ($n$=65) | $\delta$ | -5 | | -14 | | - | | - | | - | | - | | - | |
| $F_{Long_{mid}}$ | | 16% | 25% | 15% | 22% | - | - | - | - | - | - | - | - | - | - |
| ($n$=65) | $\delta$ | -9 | | -7 | | - | | - | | - | | - | | - | |
| $F_{Long_{hig}}$ | | 70% | 56% | 85% | 64% | - | - | - | - | - | - | - | - | - | - |
| ($n$=65) | $\delta$ | 14 | | 21 | | - | | - | | - | | - | | - | |

$Meas.$ / $Pred.$ = Measured / Predicted values
$Gold\ (TD=0/1)$ = Experiment of Gold with $TrafficDensity = 0$ / $TrafficDensity = 10$ (Section 5.2)
$Lorenz$ = Experiment of Lorenz et al. (2014) (Subsection 5.3.1)
$Zeeb$ = Experiment of Zeeb et al. (2015) (Subsection 5.3.2)
$Kerschbaum$ = Experiment of Kerschbaum et al. (2015) (Subsection 5.3.3)
$Hergeth.E/I$ = Experiment of Hergeth et al. (2016) with Experienced / Inexperienced drivers (Subsection 5.3.4)

# 6 Limitations

Research findings are restricted to the circumstances of the studies they are based on. Similarly, the findings in this thesis have a limited range of validity and must be handled with care when drawing inferences or assigning them to other settings or domains.

## 6.1 Limitation of Driving Simulator Experiments for Assessing Take-Over Performance

Assessing take-over performance in a driving simulator induces limited transferability to problems on the road, as the representation of visual, haptic, and vestibular stimuli, as well as risk perception and other factors, may differ from real vehicles. For example, accelerations must be scaled in dynamic driving simulators or are only perceived over the visual channel in fix-based driving simulators. Driving simulator experiments are less suited to record absolute values, such as absolute figures for the accelerations that occurred, in such take-over scenarios, but very well suited for relative comparisons of different systems, for example measuring the effect of different non-driving-related tasks on take-over performance. In this way, the proposed models can be used for gaining a better understanding of the take-over and factors influencing the performance, but predicted values are likely to differ when assigned to real vehicles on the road. Nevertheless, there is a good chance that only small adaptations will lead to valid models for predicting take-over performance on the road, once such data becomes available, as the model of driver's performance should remain valid, independent from the actual setting.

During the last few years, take-over research was based on a rough estimation of future system properties. Situations, HMIs, TORs and other characteristics were designed for experimental purposes and to address specific questions, but they also represent a rather generic implementation of future HAVs, probably resulting in a loss of accuracy. For example, the majority of studies consider SAE *Conditional Automation*, although these systems are rather unlikely to be applied. The setting, based on conditional automation, is still a very valuable approach for assessing human performance in HAVs and should be further pursued. Nevertheless, SAE *High Automation* is more likely to be implemented in future vehicles, and here the system features an alternative fallback level in case of an absent take-over of the driver. While very few experiments have actually implemented emergency maneuvers when participants failed to take over appropriately, this could, for instance, influence (reduce) collision probability.

In a similar way, to limit the experimental effort, automated driving only lasted a few minutes until the take-over occurred. A decrement in vigilance starts between 5 and 15 minutes (Warm, Parasuraman, & Matthews, 2008) and therefore could probably not come to light in the experiments. Longer automation periods should be examined, not least because they are addressed in very few studies in the literature, and the TORs will probably not occur that often.

A wide range of non-driving-related tasks has been considered, but they also had to be performed by the participants, regardless of their willingness to perform non-driving-related tasks while driving in automated mode. Although they proved to have a minor influence on the take-over, it is of interest what drivers engage in and to which extent when they are driving in automated mode and are free to choose an activity themselves.

A further limitation of the studies could be caused by the selection of participants, as they were mainly recruited within the university environment and among employees of BMW. This may cause a bias, which can be found in other studies as well, and might influence the validity of the results.

## 6.2 Limitation of the Model Approach

The results in this thesis are based on a very large but still limited data-set with dependencies among the predictor variables. There is no complete permutation, but a limited combination of the implemented time budget, traffic density, and so forth. Therefore, it is inevitable that new tests are likely to cause changes in the model. The selection of scenarios also plays a role, since it does not cover the whole possible spectrum, such as different weather conditions, alcohol intoxication, take-over scenarios at night, long-term effects of automated driving, sleepiness, or scenarios with a plain underload of the driver. Although the main predictors are represented in the models, different restrictions regarding the range of validity apply, as factors not present in the training data cannot be covered by the model. Studies are also limited to time-critical scenarios with a limited time budget, as these promise the best way of measuring human performance in safety-relevant take-over scenarios, and they provide important insights. Other authors pursue a different approach of uncritical take-overs with very large time budgets, which correspondingly cannot be predicted by the models.
This thesis establishes and proves a causal relationship as depicted by the models. However, significance of factors does not necessarily have to indicate a causal relationship between predictor and output parameter. It is impossible to completely rule out that predictors explaining variance are misleading and have no or little causality, although results are in line with literature and cognitive models.

# 7 Discussion

Knowing influencing factors and being able to predict take-over performance is a key aspect of HAD research; it can substitute experiments and help to cross-validate findings in this field. It can also contribute to assessing the controllability of HAVs, an important aspect, as new methods for ensuring safety in HAVs are urgently required (Winner & Wachenfeld, 2013).

**Predictor Variables**

*TimeBudget*, *TrafficDensity*, *Repetition*, and *Age* were identified as main influencing factors, and the results matched the expectations regarding their direction of influence. These predictors were significant in the majority of models. The *TimeBudget* has a strong linear influence in the considered range of 5 to 8 seconds. Raising the *TimeBudget* above this range is expected to lead to a decreasing benefit regarding performance, as above a certain threshold, following the data, more time will not further improve take-over performance. A model considering long TBs as well as short ones would most likely lead to a logarithmic trend of the *TimeBudget*, rather than a linear one. Nevertheless, for this modeling attempt, mainly time-critical take-over scenarios with certain system specifications (see also Chapter 6) were selected. This is reasonable and valuable, as the current development and design process requires information regarding human performance in such take-over scenarios, and human-machine-interaction is currently the most important requirement of HAD-related research (Gasser, 2013). With regard to the *TimeBudget*, it is remarkable that it does not show a significant effect when modeling *Crash*, probably because the number of collisions was rather small, and an imperfect permutation of factors among the experiments could not be completely avoided. Especially when further decreasing the *TimeBudget*, more crashes will occur, which is currently not represented in the model.

*TrafficDensity* was identified as a second main contributor to the response variables, as it significantly contributes to all models (except for the *GazeReactionTime* model). Furthermore, *TrafficDensity* shows an exponential behavior with a maximum between 15 and 30 vehicles/km when modeling *Crash*, *Lat.Acc.*, and *Take-OverTime*. Above this range, it shows a re-decrease in criticality for higher traffic densities, explained by quicker decision-making and braking in scenarios with very dense traffic. Of the considered scenarios, the most difficult seem to involve a medium traffic density, where the possibility to change lanes is not obvious and requires extended perception and consideration by the driver.

The predictor *Repetition* was identified as another important influencing factor on take-over time and quality aspects. A logarithmic trend was assumed and, while modeling, proved to be appropriate. *Repetition* represents learning effects and experience in take-over scenarios and is considered one of the main effects when assessing take-over performance. Training take-over scenarios showed to improve driver's performance and reduce the criticality of the situations. On the other hand, if system performance increases and the frequency of take-over scenarios decreases at the same time, drivers could experience a loss of skills and therefore re-raise the criticality of take-over situations.

A fourth factor, *Age*, proved to have a large influence in certain models, especially when modeling *GazeReactionTime* and *Lat.Acc.* In most cases, the influence of *Age* is exponential, with higher effects in young and elderly drivers, and it is lowest between 30 and 50 years. This is similar to characteristics of simple reaction times of different age groups (Kováč, 1969; Höhne, 1974) and also brings to mind crash statistics with middle-aged drivers, who are less often causing fatal crashes than other age groups (Statistisches Bundesamt, 2015). The results also indicate that elderly drivers can compensate possible age-related limitations by increased braking and thus significantly raise the take-over quality. This refutes the concern that studies involving younger drivers only draw a too positive picture.

The other predictors *Load*, *EyesOffRoad*, and *Lane* had a minor influence. *Lane* was significant for *Take-OverTime*, *Lat.Acc.*, and *TTC*, but to a small degree. This is in line with findings in the studies, where no effect of *Lane* on take-over performance was found (Radlmayr et al., 2014; Gold et al., 2014). The small effect of *Load* and *EyesOffRoad*, which map the non-driving-related task, was rather unexpected, although studies did not indicate strong effects of the tasks (Gold, Berisha, & Bengler, 2015). Partially, the correlation of *Load* and *Repetition*, caused by an imperfect variation of factors in the experiments, may have covered effects of the non-driving-related task and assign them to *Repetition*. Only in *GazeReactionTime* and *TTC* did the predictor *Load* show significant influence, whereas *EyesOffRoad* did not have an impact on any model. Furthermore, for the *TTC*, the direction of *Load* was contrary to expectations, which was separately discussed in Section 4.7.

**Models of Response Variables**

In order to model take-over performance, a number of dependent variables had to be selected. The decision for the parameter set was based on prior research, physics, cognitive science, and established surrogate safety metrics. Although this parameter set proved to provide a valid assessment of the take-over (Happee et al., 2016), other variables could also act as valid metrics. Assessment of scenarios in which only the stabilization of the vehicle has to be ensured, is limited with the current set of variables.

The validation confirmed very good predictive characteristics for *GazeReactionTime*, *Take-OverTime*, *TTC*, and *Crash*, and still good characteristic for *Lat.Acc.* Furthermore, validation indicated that the “eyes-on-road” time can also be predicted by the *GazeReactionTime* model by adding 200 ms to the model output.

Regarding brake applications, *Brake* and *Long.Acc.* deviated from the validation data to a greater extent and also showed less explained variance while modeling. These models in particular improve most when the driver is introduced as a predictor to the equations, which is why knowledge on drivers' predisposition would significantly improve models such as *GazeReactionTime*, *Lat.Acc.*, *Long.Acc.*, and *Brake* in particular. For the prediction of single responses of particular drivers, this additional knowledge is inevitable for a meaningful prediction. On the other hand, if mean values are of interest, for example if the influence of different traffic densities in a certain scenario is to be analyzed, the models presented can predict valid data for a larger group of drivers. Here, the variance between single drivers is dropped while building the group's average. Unless predispositions of drivers are known, the strength of the models is rather the prediction of responses of the population than the individual, which is also the case for most driving simulator studies. Nevertheless, if drivers are known, the proposed models can be used to predict individual take-overs of certain drivers in dependence on the situational factors.

The models are interpolation equations in the range of the explanatory variables used to fit the model, but they may not be valid for extrapolation (Montgomery & Peck, 1992). Nevertheless, if models are well adjusted and show adequacy, limited extrapolations may be feasible, which could be shown when models were compared to experiments of other authors. The prediction matched the results of the authors, even if they were located at the edge or outside the range of the training data. Overall, the validation showed that the models are not only in line with the results of other authors' research, but are also valid predictors for take-over experiments. For the first time, the models enable a unique understanding of the interaction between different predictors, as they allow a simultaneous consideration of seven predictor variables, revealing their relevance for modeling drivers' take-over performance in HAVs.

# 8 Summary

Based on the research need to ensure safety of Highly Automated Vehicles (HAVs) by assessing and understanding human performance in take-over scenarios, this thesis introduced a quantitative approach to model take-over performance in time-critical situations of Highly Automated Driving (HAD). The models assess and predict the outcome of those take-overs, which is most likely to be the most important key factor when considering controllability of HAVs. Different aspects of highly automated vehicle guidance were examined, and a broad overview of take-over research was provided. Additionally, HAD-related definitions were proposed, and relevant models of human performance and information processing recalled. In order to select a suitable approach for modeling take-over performance, a variety of methods was discussed and weighed under consideration of the research goal to achieve a valid prediction of performance and simultaneously gain knowledge on interactions of predictors and their influence on the response variables. A combination of different regression methods was selected as most appropriate and beneficial, as regression features good predictive characteristics, while disclosing the relations of the predictors.

To generate a data-set for training the models, six driving simulator studies were conducted in different high-fidelity driving simulators. The experiments contained take-over requests (TORs) in Lead Vehicle Stationary (LVS) take-over scenarios on a highway with a limited Time Budget (TB) to create demanding situations, suitable to assess drivers' performance. Previous analysis of literature and models of cognition and information processing led to the identification of seven main influencing factors regarding the take-over performance. These seven predictors, namely the *TimeBudget*, *Lane*, *TrafficDensity*, *Repetition*, *Load*, Eyes-Off-Road (*EyesOffRoad*), and *Age* were examined during the experiments. In this way, a database containing 753 valid take-overs was created. The *GazeReactionTime*, *Take-OverTime*, *Lat.Acc.*, *Long.Acc.*, *Brake*, *Crash*, and *TTC* were identified as the most promising response variables that assess timing and quality aspects of the take-over. Correlations between these measures, obstructive for the modeling process, could have been prevented to a certain degree, but not avoided completely. Although the remaining correlations are considered to be uncritical, a distortion of the models cannot be ruled out completely.

Based on literature and a preliminary data analysis, the contribution of the different parameters was supposed to have either a linear, logarithmic, or exponential influence on the response. For the different response variables, different regression methods were applied. *GazeReactionTime*, *Take-OverTime*, *Lat.Acc.*, and *TTC* were modeled by the use of non-linear regressions. For *Lat.Acc.* and *TTC* separate models for braking and non-braking drivers were implemented, improving the prediction capability of the non-braking group. In order to provide information regarding the brake probability and thus the allocation of data to the separated models for *Lat.Acc.* and *TTC*, the *Brake* model was established, a logistic model calculating brake probabilities. Additionally, logistic models for modeling the crash probability (*Crash*) and the probability of the occurrence of low, medium, and high longitudinal accelerations (*Long.Acc.*) were set up.

Only those predictors were kept in the regression equation that showed significance when evaluated by a t-test. *TimeBudget*, *TrafficDensity*, *Repetition*, and *Age* were identified as the strongest influencing predictors while *Load*, *EyesOffRoad*, and *Lane* explained minor variance with no significance in many models. The assessment of the models' adequacy showed good characteristics for the *Take-OverTime*, *TTC*, and *Crash* model. The *Lat.Acc.* models showed a slightly less accurate performance, and the *Long.Acc.* and *Brake* model were assessed to have moderate adequacy. The *GazeReactionTime* model explained only minor variance, but the model is still regarded as valuable, as the data shows only low standard deviations. The reaction times are therefore located within a narrow range, which can be predicted without the need to explain large shares of the variance within that range. The errors in some of the models were found to not always be normally distributed, but the regressions appear to be rather resilient, as generalized models that address different distributions did not improve the models' adequacy by a relevant degree. On the contrary, the established models could be further improved by reducing the effects of outliers in the data by the use of the robust weight function "Fair". A mixed-effect regression revealed a large variance induced by the drivers and significant model improvements under consideration of the drivers' predisposition. This contribution of the driver could and should be considered as a predictor, but is only available for drivers with several recorded take-overs or retrievable by driver monitoring. This data is so far not available for prediction, and the validation was performed with the less accurate driver-independent regression models.

The models' predictions were compared to a new set of data, recorded for validation in an additional driving simulator experiment. Furthermore, based on published descriptions of the experiments, the models enabled the prediction of take-over performance of four driving simulator studies of different national and international authors. Validation strengthened the modeling results and the previous assessments of models' adequacy. Prediction characteristics of the validation experiments matched the characteristics identified while modeling, as the models for *GazeReactionTime*, *Take-OverTime*, *Lat.Acc.*, *TTC*, and *Crash* were able to adequately - and in some cases very precisely - predict the results of the tested experiments, whereas *Brake* and *Long.Acc.* showed higher deviations. As validation results were in line with the modeling, validity of the models is assumed.

In conclusion, this thesis provides an effective way of estimating performance in time-critical take-over scenarios and proved the potential to even substitute driving simulator experiments, facilitating the controllability assessment of the take-over in HAVs. Furthermore, the thesis enables a profound comprehension of the effect and magnitude of different factors that influence take-over performance and for the first time facilitates their simultaneous consideration.

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# A Plots of Non-Linear Mixed Effect Models

Plot for *GazeReactionTime* can be found in Figure 4.33.

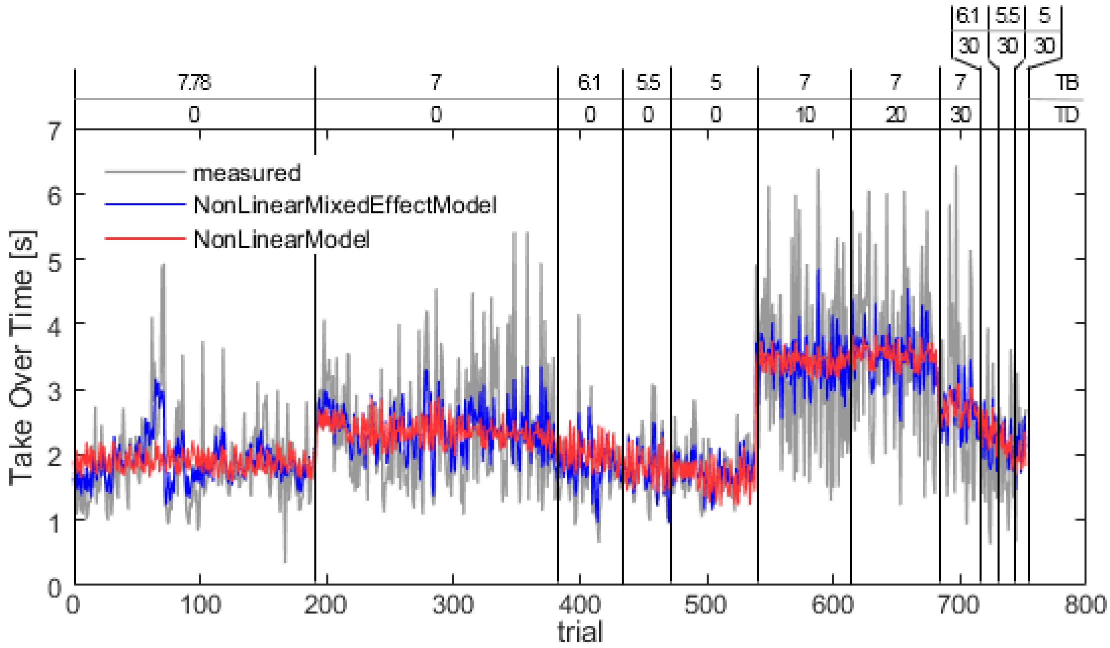


Figure A.1: Comparison of fit for *Take-OverTime* of NonLinearModel, and MixedEffectModel.

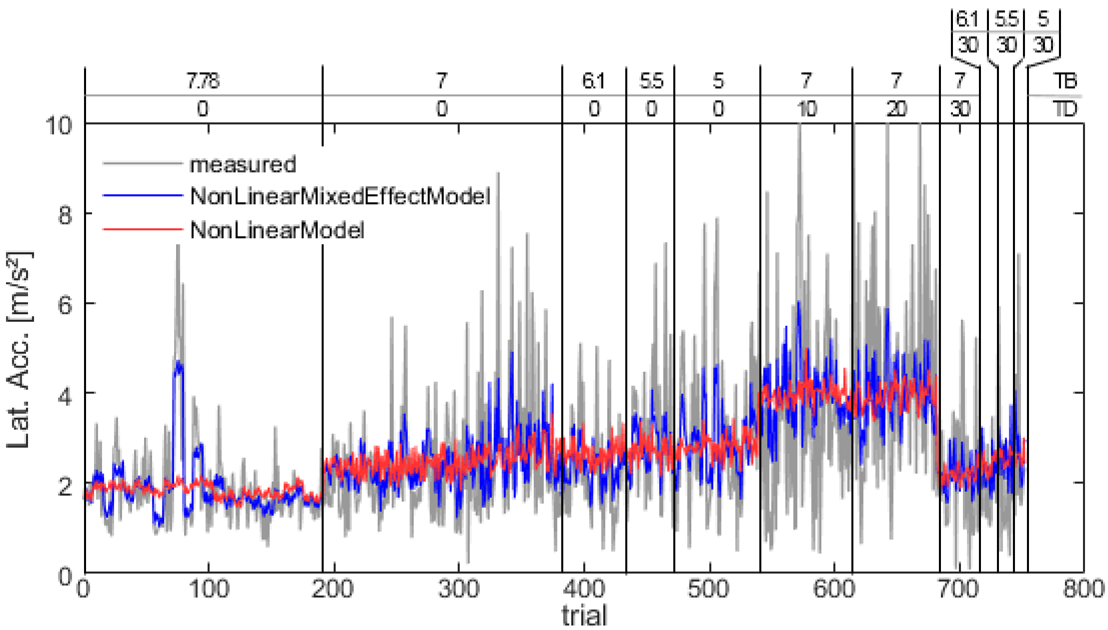


Figure A.2: Comparison of fit for *Lat.Acc.* of NonLinearModel, and MixedEffectModel.

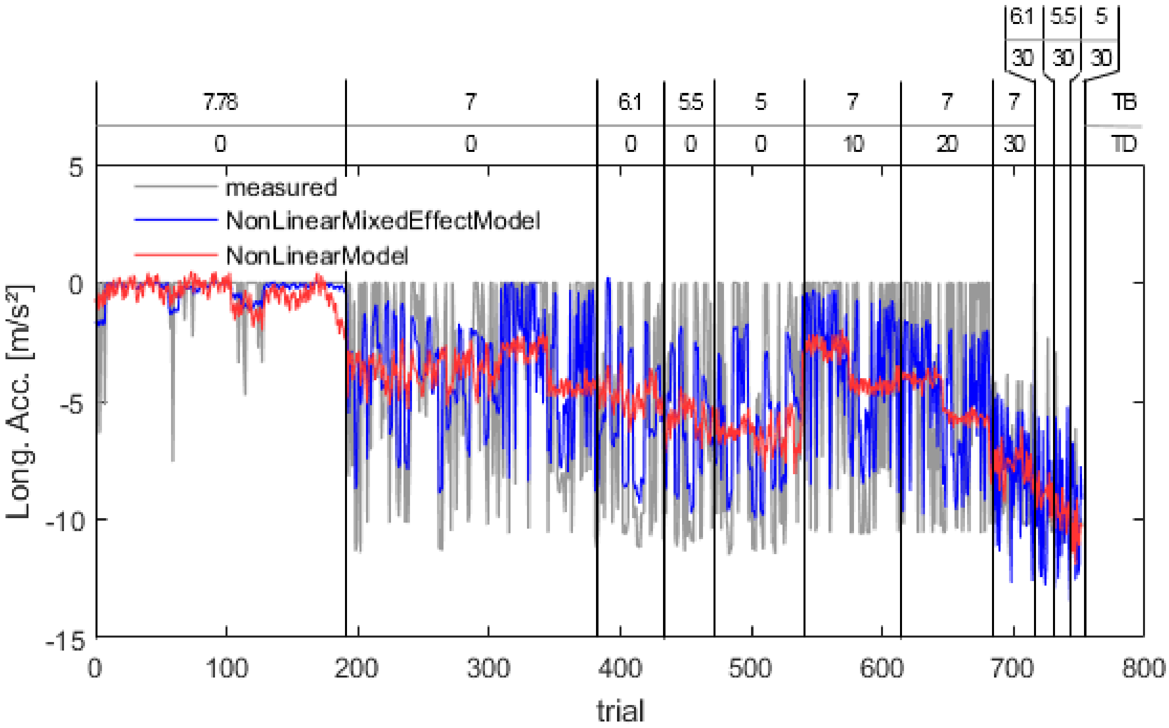


Figure A.3: Comparison of fit for *Long.Acc.* of NonLinearModel, and MixedEffectModel.

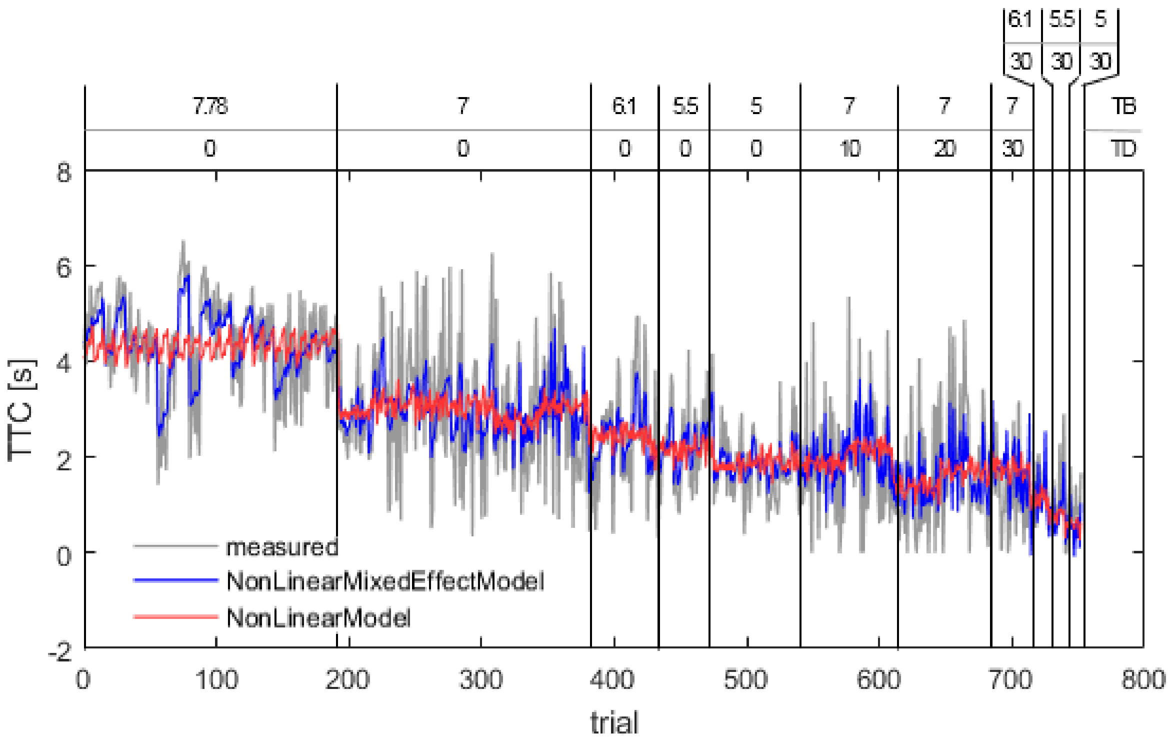


Figure A.4: Comparison of fit for *TTC* of NonLinearModel, and MixedEffectModel.

# B Regression Models for Braking and Non-Braking Drivers

$$\begin{aligned} t_{T0} &= -9.800 + 0.194 * I_{TimeBudget} + ... \\ ... &+ 0.203 * (I_{Lane} - 1.891)^2 + 0.002 * (I_{TrafficDensity} + 210.946)^2 - ... \\ ... &- 0.341 * \ln I_{Repetition} \end{aligned} \tag{B.1}$$

$$a_{Lat1} = 3.744 - 0.007 * (I_{TrafficDensity} - 14.769)^2 + 4.353 * 10^{-4} * (I_{Age} - 35.306)^2 \tag{B.2}$$

$$\begin{aligned} t_{TTC1} &= -3.584 + 0.513 * I_{TimeBudget} - ... \\ ... &- 0.082 * (I_{Lane} - 1.314)^2 + 0.0022 * (I_{TrafficDensity} - 26.086)^2 + ... \\ ... &+ 0.425 * \ln I_{Repetition} + 0.243 * I_{Load} + 0.019 * I_{Age} \end{aligned} \tag{B.3}$$

$$\begin{aligned} t_{T1} &= -8.757 + 0.286 * I_{TimeBudget} - ... \\ ... &- 1.231 * (I_{Lane} + 122.724)^2 + 5.236 * 10^{-5} * (I_{TrafficDensity} + 472.112)^2 - ... \\ ... &- 0.354 * \ln I_{Repetition} - 0.178 * I_{Load} - 0.110 * I_{EOR} \end{aligned} \tag{B.4}$$

$$\begin{aligned} a_{Lat0} &= 6.514 - 0.487 * I_{TimeBudget} + 0.343 * I_{Lane} - ... \\ ... &- 0.004 * (I_{TrafficDensity} - 17.200)^2 - 0.267 * \ln I_{Repetition} + ... \\ ... &+ 6.322 * 10^{-4} * (I_{Age} - 47.432)^2 \end{aligned} \tag{B.5}$$

$$\begin{aligned} t_{TTC0} &= -4.283 + 0.699 * I_{TimeBudget} + ... \\ ... &+ 0.0043 * (I_{TrafficDensity} - 17.518)^2 + ... \\ ... &+ 0.521 * \ln I_{Repetition} + 0.148 * I_{Load} \end{aligned} \tag{B.6}$$

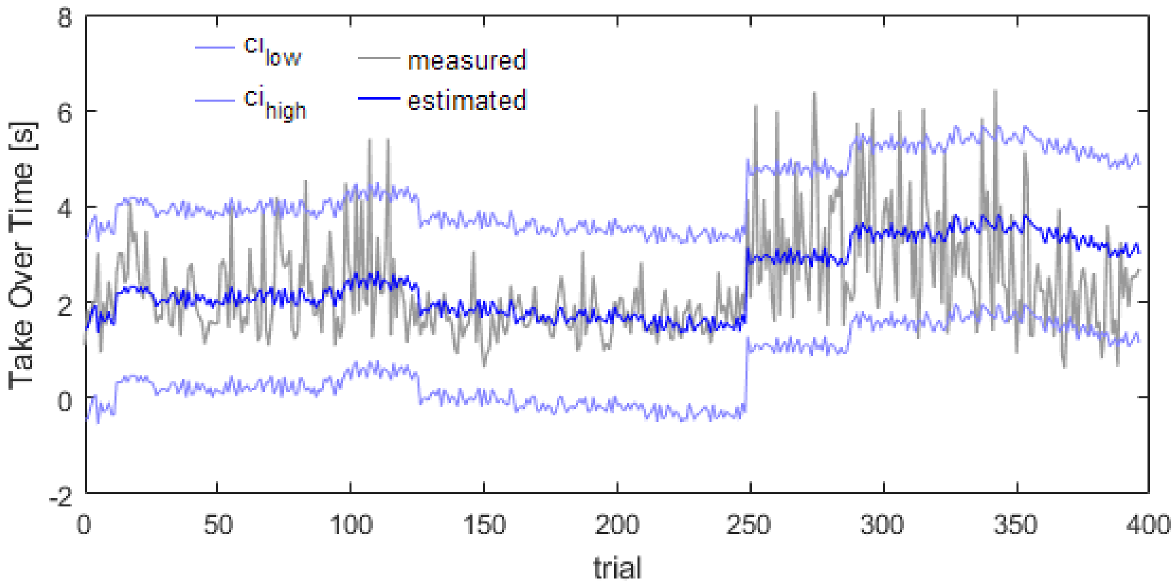


Figure B.1: Estimation and measures of *Take-OverTime* for braking drivers.

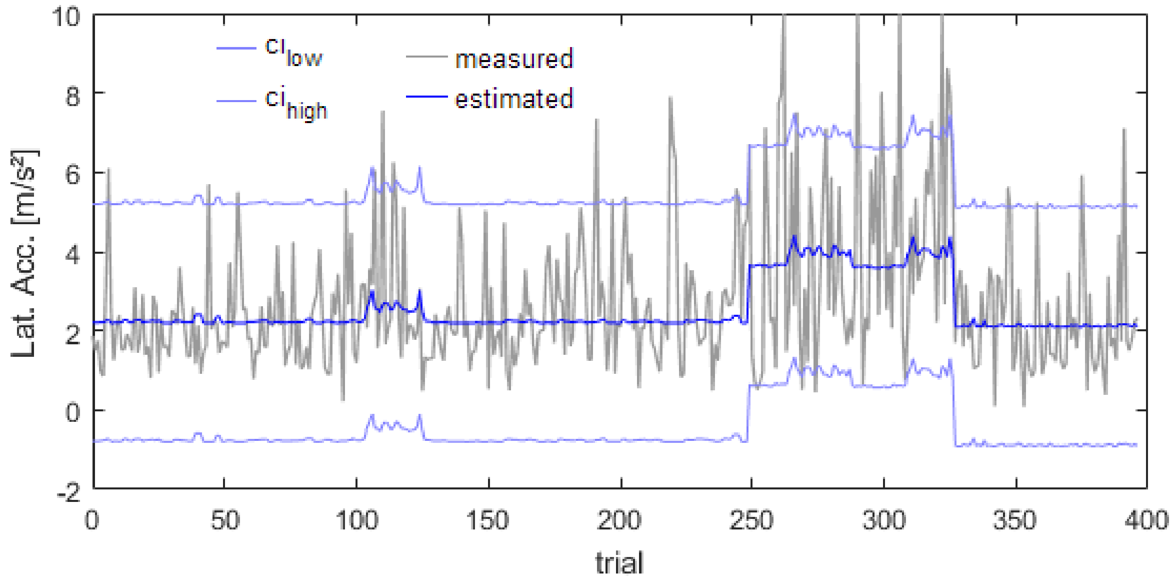


Figure B.2: Estimation and measures of *Lat.Acc.* for braking drivers.

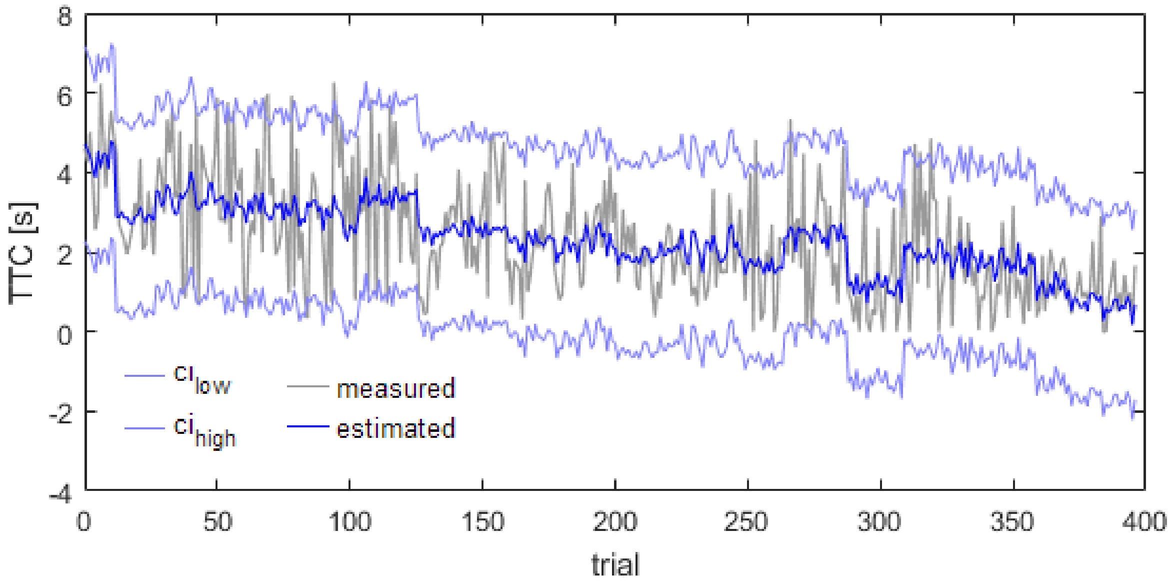


Figure B.3: Estimation and measures of $TTC$ for braking drivers.

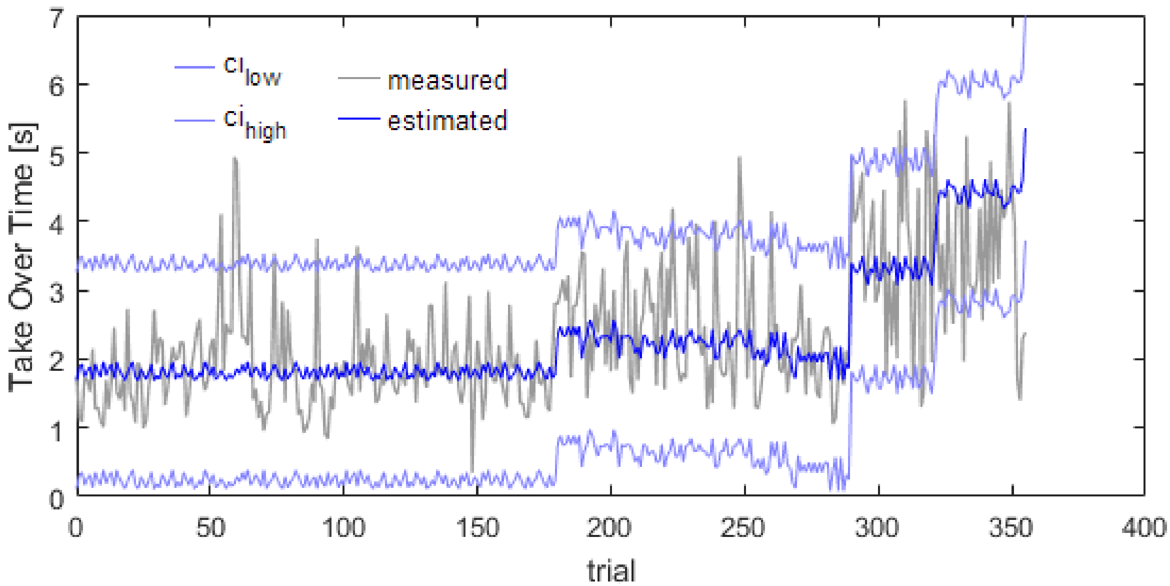


Figure B.4: Estimation and measures of *Take-OverTime* for non-braking drivers.

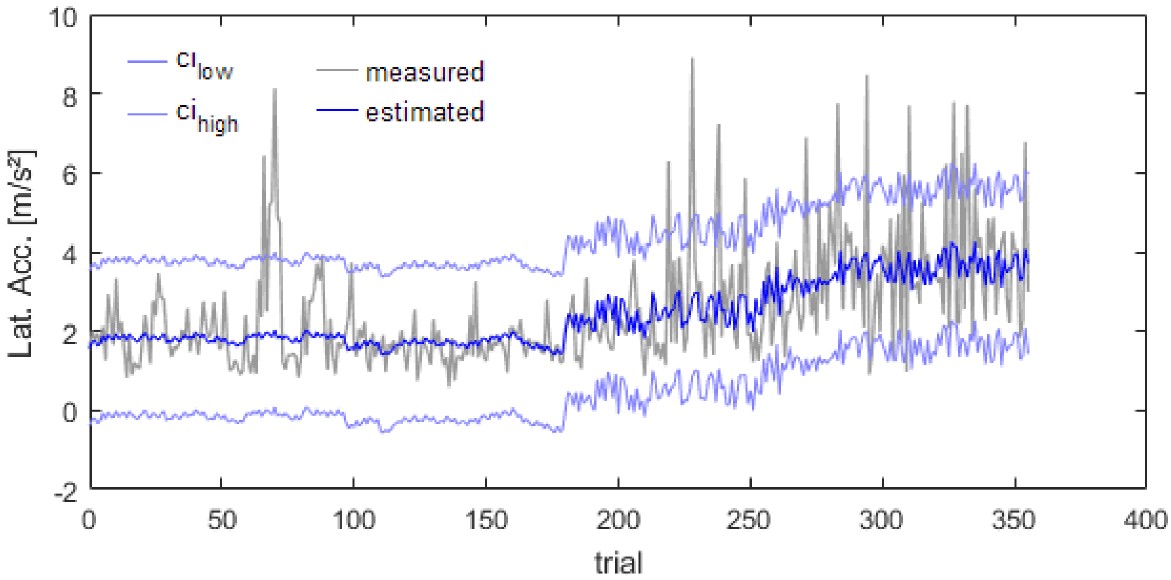


Figure B.5: Estimation and measures of $Lat.Acc.$ for non-braking drivers.

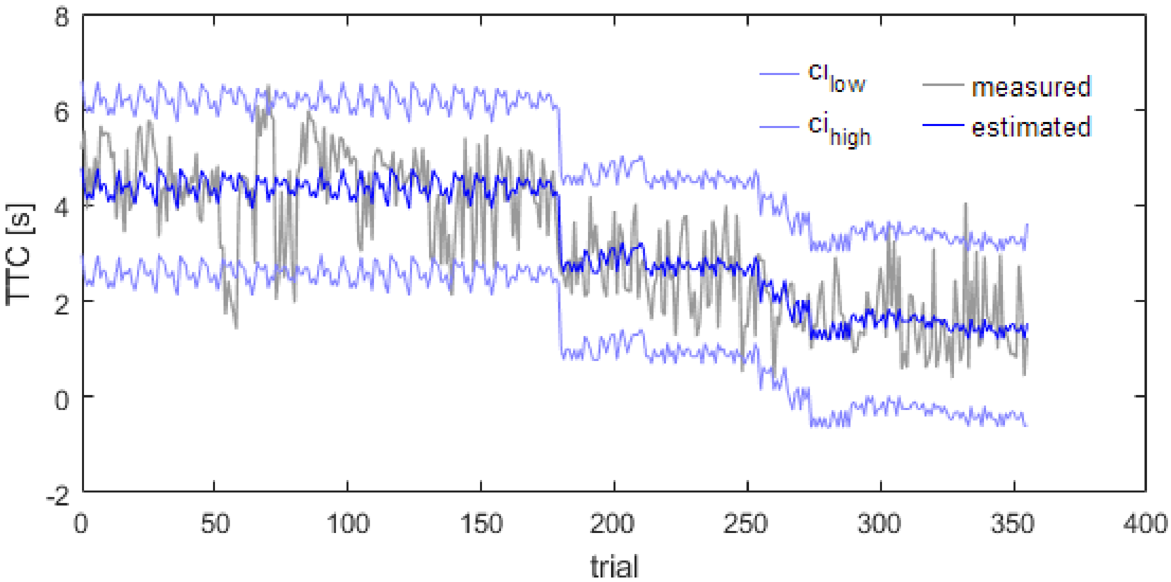


Figure B.6: Estimation and measures of $TTC$ for non-braking drivers.

# C Plots of Validation Data

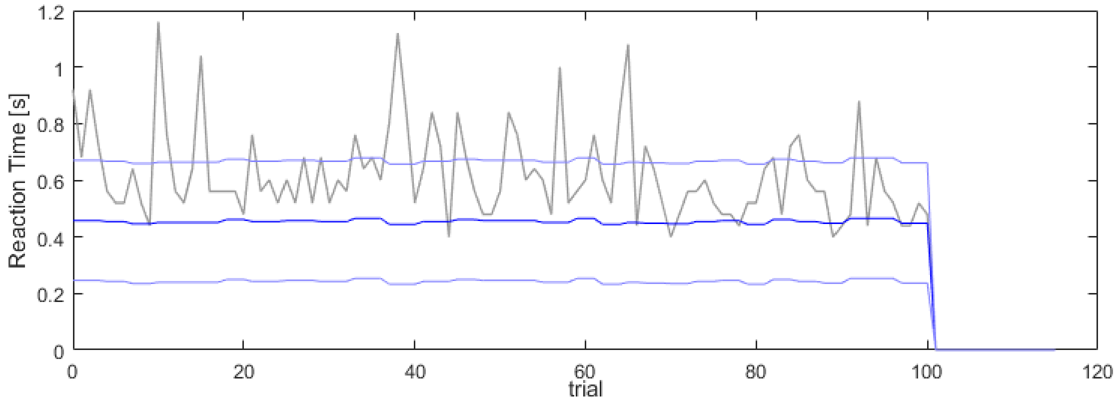


Figure C.1: Estimation and measures of *GazeReactionTime* for validation data.

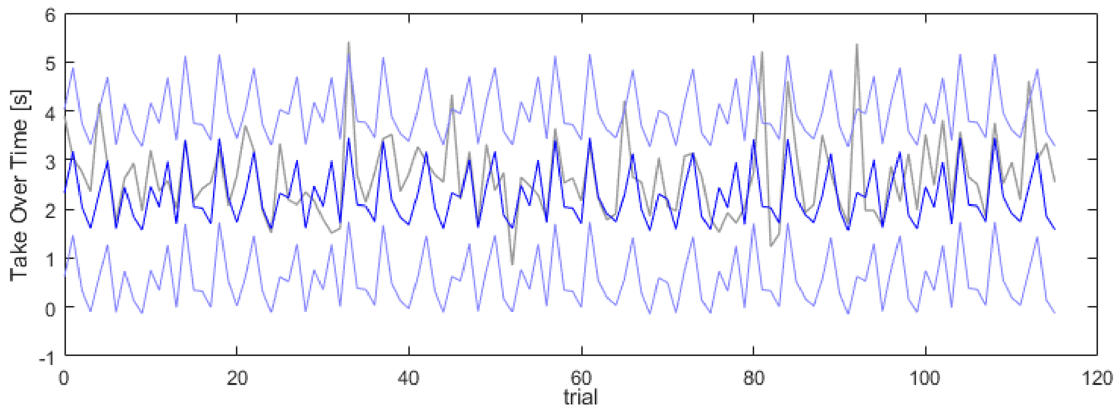


Figure C.2: Estimation and measures of *Take-OverTime* for validation data.

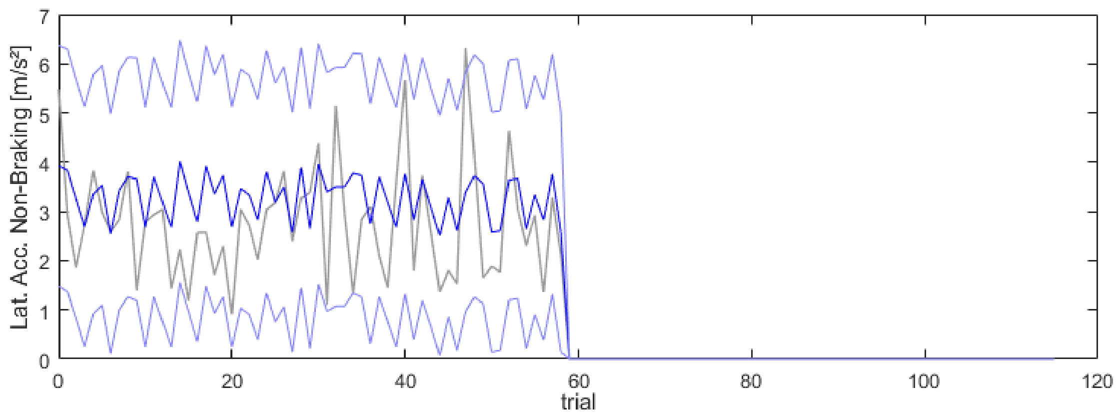


Figure C.3: Estimation and measures of *Lat.Acc.* for validation data of non-braking drivers.

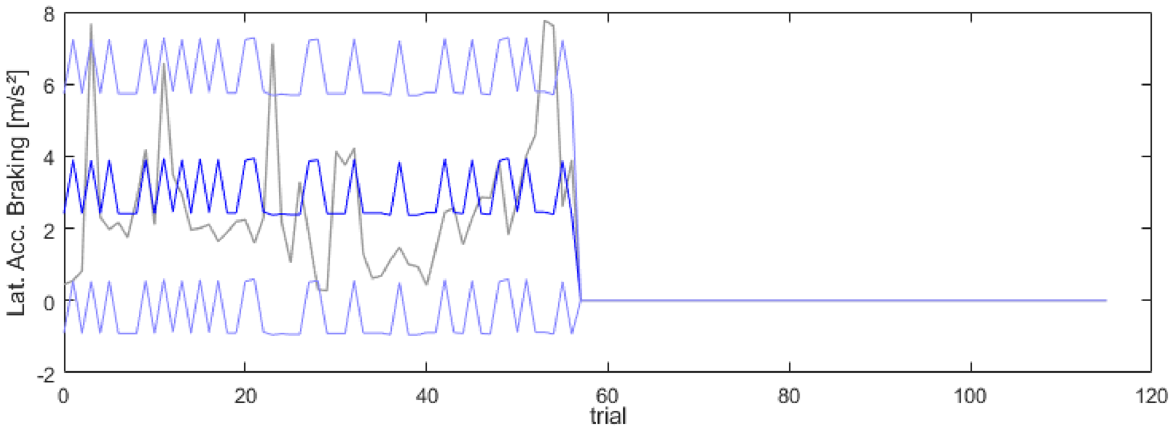


Figure C.4: Estimation and measures of $Lat.Acc.$ for validation data of braking drivers.

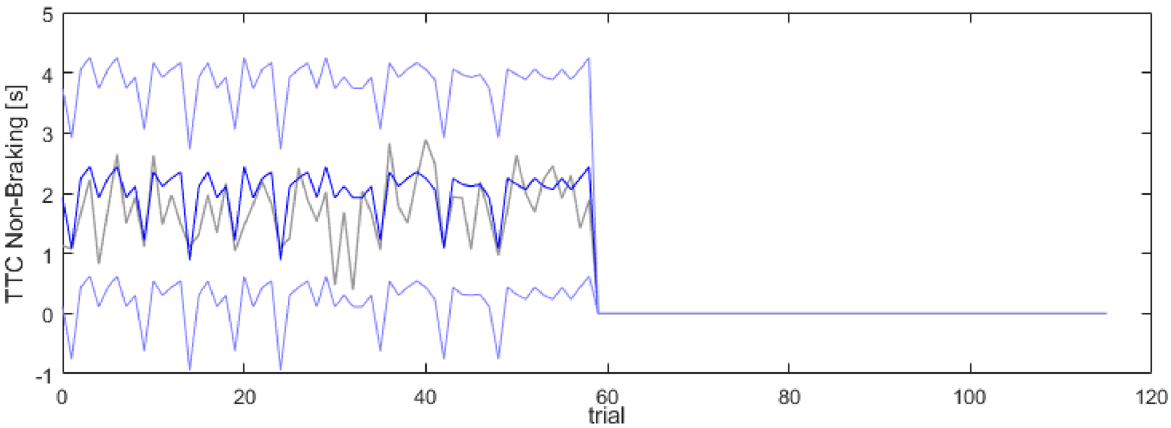


Figure C.5: Estimation and measures of $TTC$ for validation data of non-braking drivers.

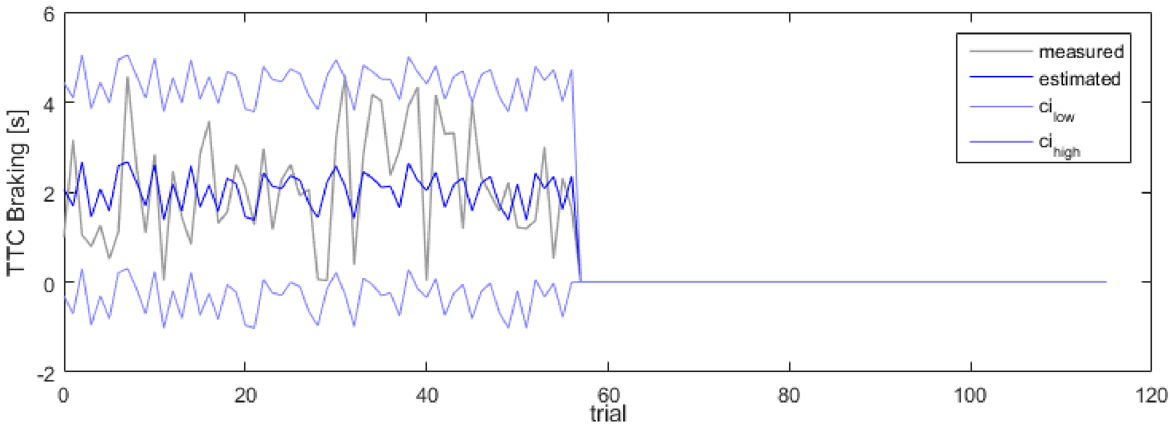


Figure C.6: Estimation and measures of $TTC$ for validation data of braking drivers.

# D Matlab Code

```
%% Modeling Take-Over Performance of Highly Automated Vehicles
%   Matlab source code of the dissertational thesis of Christian Gold,
%   Institute of Ergonomics, Technical University of Munich.
% *** Introduction to the structure
%   MLETakeover.m
%   * Main code file
%   * Includes main body of source code
%   * Estimated several take-over performance metrics and creates models output
%   fcndataconfig
%   * Includes config files and data bases
%       config.m
%       * Includes definitions and user input mask
%       estnlme.m
%       * Estimation of Non-Linear-Mixed-Effect models
%       models.m
%       * Model equations
%       valconfig.m
%       * Configuration file for validation data
%   fcnplot
%   * Includes functions for the purpose of plotting the results
%   fcnval
%   * Includes functions for validation purpose
% *** Author and affiliation:
%   * Christian Gold, Institute of Ergonomics, TUM
%   * Inspired by code of:
%   *   Sembiring, Javensius
%   *   Institute of Flight System Dynamics, TUM
% *** Bug or revision, please contact:
%   * gold@lfe.mw.tum.de
% *** Instruction:
%   * all user input is required in config.m

%% m-file implementation
clear; %Setting up a clear workspace
clc; %clear

fprintf('Defining workspace...\n');
workingdir = {'fcnplot','fcndataconfig','fcnval'};

for i = 1:length(workingdir) %Add pathes of working directories
    addpath(workingdir{i});
end

fprintf('Loading Config...\n');
[data,label,con] = feval('config'); % *** load data and plot configuration

%% Nominal Regressions
fprintf('Calculating Nominal Regression for Braking (all cases)...\n');
[B.beta,B.dev,B.stats] = mnrfit(data.in_brake,data.brake_ord,'model','ordinal'); %calculate regression model
B.est = mnrval(B.beta,data.in_brake); %calculate probabilities for plotting braking regression
fprintf('Calculating Nominal Regression for Crashes (all cases)...\n');
[C.beta,C.dev,C.stats] = mnrfit(data.in_crash,data.crash_ord,'model','ordinal'); %calculate regression model
C.est = mnrval(C.beta,data.in_crash); %calculate probabilities for plotting crash regression
fprintf('Calculating Nominal Regression for Crashes (non-braking drivers)...\n');
[C0,devC0,statsC0] = mnrfit(data.in_crash0,data.crash_ord0,'model','ordinal'); %calculate regression model
est_crash0 = mnrval(C0,data.in_crash0); %calculate probabilities for plotting crash regression
fprintf('Calculating Nominal Regression for Crashes (braking drivers)...\n');
[C1,devC1,statsC1] = mnrfit(data.in_crash1,data.crash_ord1,'model','ordinal'); %calculate regression model
est_crash1 = mnrval(C1,data.in_crash1); %calculate probabilities for plotting crash regression

if con.Multinomial == 1
    fprintf('Calculating Nominal Regression for Lateral Accelerations (all cases)...\n');
    [LA.b,LA.dev,LA.stats] = mnrfit(data.in_lat,data.lat_ord,'model','ordinal'); %calculate regression model
    LA.est = mnrval(LA.b,data.in_lat,LA.stats,'model','ordinal'); %calculate probabilities for plotting lateral accelerations
    fprintf('Calculating Nominal Regression for Longitudinal Accelerations (all cases)...\n');
```

```
    [LO.b,LO.dev,LO.stats] = mnrfit(data.in_long,data.long_ord,'model','ordinal'); %calculate regression model
    LO.est = mnrval(LO.b,data.in_long,LO.stats,'model','ordinal'); %calculate probabilities for plotting lateral accelerations
    fprintf('Calculating Nominal Regression for Longitudinal Accelerations (braking drivers)...\n');
    [LO1.b,LO1.dev,LO1.stats] = mnrfit(data.in_long1,data.long1_ord,'model','ordinal'); %calculate regression model
    LO1.est = mnrval(LO1.b,data.in_long1,LO1.stats,'model','ordinal'); %calculate probabilities for plotting lateral accelerations
end

%% Non Linear Regressions
fprintf('Setting Parameters...\n');
stats = statset('TolX',1e-4,'TolFun',1e-4,'MaxIter',200); %Sets parameters for nlmefit
fprintf('Loading all models...\n');
[model] = models(); %load models

%Fitting Reaction Times
%for all cases where eyes were off road (eor = 1)
fprintf('Calculating Nonlinear Mixed Effect Regression for Reaction Time (all cases)...\n');
[nlme_r.b,nlme_r.PSI,nlme_r.stats,nlme_r.random] = nlmefit(data.in_eor,data.out_eor(:,1),data.participant_eor,[],model.r.m,model.r.↙
s,'REParamsSelect',1,'Options',stats);
[nlme_r.mu,nlme_r.sigma] = normfit(nlme_r.random); %Calculating normal distribution parameters for estimated random effects
fprintf('Calculating Nonlinear Regression for Reaction Time (all cases)...\n');
nl_r = fitnlm(data.in_eor,data.out_eor(:,1),model.r.m,model.r.s,'Options',con.optsr);
%for non braking drivers (eor = 1)
fprintf('Calculating Nonlinear Mixed Effect Regression for Reaction Time (non-braking drivers)...\n');
%[nlme_r0,PSIr0,statsr0,zufallr0] = nlmefit(data.in_eor0,data.out_eor0(:,1),data.participant_eor0,[],model.r0,start.r0,'REParamsSelect',↙
[1],'Options',stats);
%fprintf('Calculating Nonlinear Regression for Reaction Time (non-braking driver)...\n');
%nl_r0 = fitnlm(data.in_eor0,data.out_eor0(:,1),model.r0.m,model.r0.s,'Options',con.optsr);
%for braking drivers (eor = 1)
%fprintf('Calculating Nonlinear Mixed Effect Regression for Reaction Time (braking drivers)...\n');
%[nlme_r1,PSIr1,statsr1,zufallr1] = nlmefit(data.in_eor1,data.out_eor1(:,1),data.participant_eor1,[],model.r1,start.r1,'REParamsSelect',↙
[1],'Options',stats);
%fprintf('Calculating Nonlinear Regression for Reaction Time (braking drivers)...\n');
%nl_r1 = fitnlm(data.in_eor1,data.out_eor1(:,1),model.r1.m,model.r1.s,'Options',con.optsr);

%Fitting Take Over Times
fprintf('Calculating Nonlinear Mixed Effect Regression for Take Over Time (all cases)...\n');
[nlme_t.b,nlme_t.PSI,nlme_t.stats,nlme_t.random] = nlmefit(data.in,data.out(:,2),data.participant,[],model.t.m,model.t.s,'REParamsSelect',↙
1,'Options',stats,'RefineBeta0','off');
[nlme_t.mu,nlme_t.sigma] = normfit(nlme_t.random); %Calculating normal distribution parameters for estimated random effects
fprintf('Calculating Nonlinear Regression for Take Over Time (all cases)...\n');
nl_t = fitnlm(data.in,data.out(:,2),model.t.m,model.t.s,'Options',con.optst);
fprintf('Calculating Nonlinear Mixed Effect Regression for Take Over Time (non-braking drivers)...\n');
%[nlme_t0,PSIt0,statst0,zufallt0] = nlmefit(data.in0,data.out0(:,2),data.participant0,[],model.t0,start.t0,'REParamsSelect',[1],'Options',↙
stats,'RefineBeta0','off');
fprintf('Calculating Nonlinear Regression for Take Over Time (non-braking driver)...\n');
nl_t0 = fitnlm(data.in0,data.out0(:,2),model.t0.m,model.t0.s,'Options',con.optst);
fprintf('Calculating Nonlinear Mixed Effect Regression for Take Over Time (braking drivers)...\n');
%[nlme_t1,PSIt1,statst1,zufallt1] = nlmefit(data.in1,data.out1(:,2),data.participant1,[],model.t1,start.t1,'REParamsSelect',[1],'Options',↙
stats,'RefineBeta0','off');
fprintf('Calculating Nonlinear Regression for Take Over Time (braking drivers)...\n');
nl_t1 = fitnlm(data.in1,data.out1(:,2),model.t1.m,model.t1.s,'Options',con.optst);

%Fitting Lateral Accelerations
fprintf('Calculating Nonlinear Mixed Effect Regression for Lateral Accelerations (all cases)...\n');
[nlme_lat.b,nlme_lat.PSI,nlme_lat.stats,nlme_lat.random] = nlmefit(data.in,data.out(:,3),data.participant,[],model.lat.m,model.lat.↙
s,'REParamsSelect',1,'Options',stats,'RefineBeta0','off');
[nlme_lat.mu,nlme_lat.sigma] = normfit(nlme_lat.random); %Calculating normal distribution parameters for estimated random effects
fprintf('Calculating Nonlinear Regression for Lateral Accelerations (all cases)...\n');
nl_lat = fitnlm(data.in,data.out(:,3),model.lat.m,model.lat.s,'Options',con.optslat);
fprintf('Calculating Nonlinear Mixed Effect Regression for Lateral Accelerations (non-braking drivers)...\n');
%[nlme_lat0,PSIlat0,statslat0,zufalllat0] = nlmefit(data.in0,data.out0(:,3),data.participant0,[],model.lat0,start.lat0,'REParamsSelect',↙
[1],'Options',stats,'RefineBeta0','off');
fprintf('Calculating Nonlinear Regression for Lateral Accelerations (non-braking driver)...\n');
nl_lat0 = fitnlm(data.in0,data.out0(:,3),model.lat0.m,model.lat0.s,'Options',con.optslat);
fprintf('Calculating Nonlinear Mixed Effect Regression for Lateral Accelerations (braking drivers)...\n');
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```
%[nlme_lat1,PSIlat1,statslat1,zufalllat1] = nlmefit(data.in1,data.out1(:,3),data.participant1,[],model.lat1,start.lat1,'REParamsSelect',↙
[1],'Options',stats,'RefineBeta0','off');
fprintf('Calculating Nonlinear Regression for Lateral Accelerations (braking drivers)...\n');
nl_lat1 = fitnlm(data.in1,data.out1(:,3),model.lat1.m,model.lat1.s,'Options',con.optslat);

%Fitting Longitudinal Accelerations
fprintf('Calculating Nonlinear Mixed Effect Regression for Longitudinal Accelerations (all cases)...\n');
[nlme_long.b,nlme_long.PSI,nlme_long.stats,nlme_long.random] = nlmefit(data.in,data.out(:,4),data.participant,[],model.long.m,model.long.↙
s,'REParamsSelect',1,'Options',stats,'RefineBeta0','off');
[nlme_long.mu,nlme_long.sigma] = normfit(nlme_long.random); %Calculating normal distribution parameters for estimated random effects
fprintf('Calculating Nonlinear Regression for Longitudinal Accelerations (all cases)...\n');
nl_long = fitnlm(data.in,data.out(:,4),model.long.m,model.long.s,'Options',con.optslong);
%for braking drivers
%fprintf('Calculating Nonlinear Mixed Effect Regression for Longitudinal Accelerations (braking drivers)...\n');
%[nlme_long1,PSIlong1,statslong1,zufalllong1] = nlmefit(data.in1,data.out1(:,4),data.participant1,[],model.long1,start.↙
long1,'REParamsSelect',[1],'Options',stats,'RefineBeta0','off');
%fprintf('Calculating Nonlinear Regression for Longitudinal Accelerations (braking driver)...\n');
%nl_long1 = fitnlm(data.in1,data.out1(:,4),model.long1.m,model.long1.s,'Options',con.optslong);

%Fitting TTC
fprintf('Calculating Nonlinear Mixed Effect Regression for TTC (all cases)...\n');
[nlme_ttc.b,nlme_ttc.PSI,nlme_ttc.stats,nlme_ttc.random] = nlmefit(data.in,data.out(:,5),data.participant,[],model.ttc.m,model.ttc.↙
s,'REParamsSelect',1,'Options',stats,'RefineBeta0','off');
[nlme_ttc.mu,nlme_ttc.sigma] = normfit(nlme_ttc.random); %Calculating normal distribution parameters for estimated random effects
fprintf('Calculating Nonlinear Regression for TTC (all cases)...\n');
nl_ttc = fitnlm(data.in,data.out(:,5),model.ttc.m,model.ttc.s,'Options',con.optsttc);
fprintf('Calculating Nonlinear Mixed Effect Regression for TTC (non-braking drivers)...\n');
%[nlme_ttc0,PSIttc0,statsttc0,zufallttc1] = nlmefit(data.in0,data.out0(:,5),data.participant0,[],model.ttc0,start.ttc0,'REParamsSelect',↙
[1],'Options',stats,'RefineBeta0','off');
fprintf('Calculating Nonlinear Regression for TTC (non-braking driver)...\n');
nl_ttc0 = fitnlm(data.in0,data.out0(:,5),model.ttc0.m,model.ttc0.s,'Options',con.optsttc);
fprintf('Calculating Nonlinear Mixed Effect Regression for TTC (braking drivers)...\n');
%[nlme_ttc1,PSIttc1,statsttc1,zufallttc2] = nlmefit(data.in1,data.out1(:,5),data.participant1,[],model.ttc1,start.ttc1,'REParamsSelect',↙
[1],'Options',stats,'RefineBeta0','off');
fprintf('Calculating Nonlinear Regression for TTC (braking drivers)...\n');
nl_ttc1 = fitnlm(data.in1,data.out1(:,5),model.ttc1.m,model.ttc1.s,'Options',con.optsttc);
fprintf('Calculationg Generalized Linear Model for Take Over Time...\n');
glm_t = fitglm(data.in_lin_t, data.out(:,2), 'distribution' , 'gamma');
glm_t_RMSE = sqrt(1/753*sum(glm_t.Residuals.Raw.^2));
fprintf('Calculationg Generalized Linear Model for Take Lateral Accelerations...\n');
glm_lat = fitglm(data.in_lin_lat, data.out(:,3), 'distribution' , 'inverse gaussian');
glm_lat_RMSE = sqrt(1/753*sum(glm_lat.Residuals.Raw.^2));


%% Predict take-over parameters based on the models
[val] = feval('valconfig',con.exp); %load validation data
fprintf('Predicting means and confidence intervals, based on the calculated models...\n');
[est_r,est_r_ci] = predict(nl_r,data.in_eor, 'Prediction','observation');
%[est_r0,est_r0_ci] = predict(nl_r0,data.in_eor0, 'Prediction','observation');
%[est_r1,est_r1_ci] = predict(nl_r1,data.in_eor1, 'Prediction','observation');
[est_t,est_t_ci] = predict(nl_t,data.in, 'Prediction','observation');
[est_t0,est_t0_ci] = predict(nl_t0,data.in0, 'Prediction','observation');
[est_t1,est_t1_ci] = predict(nl_t1,data.in1, 'Prediction','observation');
[est_lat,est_lat_ci] = predict(nl_lat,data.in, 'Prediction','observation');
[est_lat0,est_lat0_ci] = predict(nl_lat0,data.in0, 'Prediction','observation');
[est_lat1,est_lat1_ci] = predict(nl_lat1,data.in1, 'Prediction','observation');
[est_long,est_long_ci] = predict(nl_long,data.in, 'Prediction','observation');
%[est_long1,est_long1_ci] = predict(nl_long1,data.in1, 'Prediction','observation');
[est_ttc,est_ttc_ci] = predict(nl_ttc,data.in, 'Prediction','observation');
[est_ttc0,est_ttc0_ci] = predict(nl_ttc0,data.in0, 'Prediction','observation');
[est_ttc1,est_ttc1_ci] = predict(nl_ttc1,data.in1, 'Prediction','observation');

fprintf('Predicting means and confidence intervals of validation data, based on the calculated models...\n');
[est_val_r,est_val_r_ci] = predict(nl_r,val.in_eor, 'Prediction','observation');
%[est_val_r0,est_val_r0_ci] = predict(nl_r0,val.in0, 'Prediction','observation');
```

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%[est_val_r1,est_val_r1_ci] = predict(nl_r1,val.in1, 'Prediction','observation');
[est_val_t,est_val_t_ci] = predict(nl_t,val.in, 'Prediction','observation');
[est_val_t0,est_val_t0_ci] = predict(nl_t0,val.in0, 'Prediction','observation');
[est_val_t1,est_val_t1_ci] = predict(nl_t1,val.in1, 'Prediction','observation');
[est_val_lat,est_val_lat_ci] = predict(nl_lat,val.in, 'Prediction','observation');
[est_val_lat0,est_val_lat0_ci] = predict(nl_lat0,val.in0, 'Prediction','observation');
[est_val_lat1,est_val_lat1_ci] = predict(nl_lat1,val.in1, 'Prediction','observation');
[est_val_long,est_val_long_ci] = predict(nl_long,val.in, 'Prediction','observation');
%[est_val_long1,est_val_long1_ci] = predict(nl_long1,val.in1, 'Prediction','observation');
[est_val_ttc,est_val_ttc_ci] = predict(nl_ttc,val.in, 'Prediction','observation');
[est_val_ttc0,est_val_ttc0_ci] = predict(nl_ttc0,val.in0, 'Prediction','observation');
[est_val_ttc1,est_val_ttc1_ci] = predict(nl_ttc1,val.in1, 'Prediction','observation');

fprintf('Estimating Brake and Crash Probabilities of Validation Data...\n');
est_brake_val = mnrval(B.beta,val.in_brake); %calculate estimated braking probabilities
est_brake_val_total = mean(est_brake_val(:,1)); %mean estimated brake probability of all validation lines
est_crash_val = mnrval(C.beta,val.in_crash); %calculate estimated braking probabilities
est_crash_val_total = mean(est_crash_val(:,1)); %mean estimated brake probability of all validation lines
est_crash0_val = mnrval(C0,val.in_crash0); %calculate estimated braking probabilities
est_crash0_val_total = mean(est_crash0_val(:,1)); %mean estimated brake probability of all validation lines
est_crash1_val = mnrval(C1,val.in_crash1); %calculate estimated braking probabilities
est_crash1_val_total = mean(est_crash1_val(:,1)); %mean estimated brake probability of all validation lines

fprintf('Estimating Data of NLME...\n');
in_datasort = [data.participant data.in];
out_datasort = [data.participant data.out];
in_datasort_eor = [data.participant_eor data.in_eor];
out_datasort_eor = [data.participant_eor data.out_eor];
[nlme_r.est, nlme_r.R, nlme_r.R_adj] = estnlme(in_datasort_eor, out_datasort_eor, 1, nlme_r.random, model.r.m, model.r.k, nlme_r.b, nl_r.↙
NumObservations); %estimate reaction time
[nlme_t.est, nlme_t.R, nlme_t.R_adj] = estnlme(in_datasort, out_datasort,2, nlme_t.random, model.t.m, model.t.k, nlme_t.b, data.n); %estimate↙
take-over-time
[nlme_lat.est, nlme_lat.R, nlme_lat.R_adj] = estnlme(in_datasort, out_datasort,3, nlme_lat.random, model.lat.m, model.lat.k, nlme_lat.b, data.↙
n); %estimate lateral accelerations
[nlme_long.est, nlme_long.R, nlme_long.R_adj] = estnlme(in_datasort, out_datasort,4, nlme_long.random, model.long.m, model.long.k,↙
nlme_long.b, data.n); %estimate longitudinal accelerations
[nlme_ttc.est, nlme_ttc.R, nlme_ttc.R_adj] = estnlme(in_datasort, out_datasort,5, nlme_ttc.random, model.ttc.m, model.ttc.k, nlme_ttc.b, data.↙
n); %estimate time to collision

%% Validation

fprintf('Calculating RMSE of Validation Data...\n');
%Calculate R and RMSE for validation data and compares results to training data
%Not valid for robust regression functions
[val.rmse.r] = valrmse(est_r, est_val_r, data.out_eor(:,1), val.out_eor(:,1));
[val.rmse.t] = valrmse(est_t, est_val_t, data.out(:,2), val.out(:,2));
[val.rmse.lat0] = valrmse(est_lat0, est_val_lat0, data.out0(:,3), val.out0(:,3));
[val.rmse.lat1] = valrmse(est_lat1, est_val_lat1, data.out1(:,3), val.out1(:,3));
[val.rmse.ttc0] = valrmse(est_ttc0, est_val_ttc0, data.out0(:,5), val.out0(:,5));
[val.rmse.ttc1] = valrmse(est_ttc1, est_val_ttc1, data.out1(:,5), val.out1(:,5));

B.est_val = mnrval(B.beta,val.in_brake); %calculate probabilities for plotting braking regression
C.est_val = mnrval(C.beta,val.in_crash); %calculate probabilities for plotting braking regression
LO1.est_val = mnrval(LO1.b,val.in_long1,LO1.stats,'model','ordinal'); %calculate probabilities for plotting braking regression

%The following is only useful if validation data is "Thesis", otherwise quitting.
if con.exp > 1
  fprintf('Foreign validation file, quitting without printing results!\n');
  return;
end

fprintf('Calculating whether validation data is located within the confidence intervals...\n');
[withinci.r,withinci.r_per] = valwithinci(length(val.in_eor),est_val_r_ci,val.out_eor(:,1));
[withinci.t,withinci.t_per] = valwithinci(val.n,est_val_t_ci,val.out(:,2));
[withinci.lat0,withinci.lat0_per] = valwithinci(val.n0,est_val_lat0_ci,val.out0(:,3));
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[withinci.lat1,withinci.lat1_per] = valwithinci(val.n1,est_val_lat1_ci,val.out1(:,3));
[withinci.ttc0,withinci.ttc0_per] = valwithinci(val.n0,est_val_ttc0_ci,val.out0(:,5));
[withinci.ttc1,withinci.ttc1_per] = valwithinci(val.n1,est_val_ttc1_ci,val.out1(:,5));

fprintf('Sorting Validation Data for easy calculation of mean and SD...\n');
meansd.tBC_data = [est_val_t B.est_val(:,2) C.est_val(:,2) est_val_t_ci(:,2)];
meansd.tBC_data_td0 = meansd.tBC_data(1:val.n_td0,:);
meansd.tBC_data_td10 = meansd.tBC_data((val.n_td0+1):val.n,:);
meansd.latttc0_data = [est_val_lat0 est_val_ttc0 est_val_lat0_ci(:,2) est_val_ttc0_ci(:,2)];
meansd.latttc0_data_td0 = meansd.latttc0_data(1:val.n_td0_br0,:);
meansd.latttc0_data_td10 = meansd.latttc0_data((val.n_td0_br0+1):val.n0,:);
meansd.latlongttc1_data = [est_val_lat1 LO1.est_val est_val_ttc1 est_val_lat1_ci(:,2) est_val_ttc1_ci(:,2)];
meansd.latlongttc1_data_td0 = meansd.latlongttc1_data(1:val.n_td0_br1,:);
meansd.latlongttc1_data_td10 = meansd.latlongttc1_data((val.n_td0_br1+1):val.n1,:);
fprintf('Calculating mean...\n');
meansd.m.ttd0 = mean(meansd.tBC_data_td0(:,1));
meansd.m.ttd10 = mean(meansd.tBC_data_td10(:,1));
meansd.m.Btd0 = mean(meansd.tBC_data_td0(:,2));
meansd.m.Btd10 = mean(meansd.tBC_data_td10(:,2));
meansd.m.Ctd0 = mean(meansd.tBC_data_td0(:,3));
meansd.m.Ctd10 = mean(meansd.tBC_data_td10(:,3));
meansd.m.lat0td0 = mean(meansd.latttc0_data_td0(:,1));
meansd.m.ttc0td0 = mean(meansd.latttc0_data_td0(:,2));
meansd.m.lat0td10 = mean(meansd.latttc0_data_td10(:,1));
meansd.m.ttc0td10 = mean(meansd.latttc0_data_td10(:,2));
meansd.m.lat1td0 = mean(meansd.latlongttc1_data_td0(:,1));
meansd.m.ttc1td0 = mean(meansd.latlongttc1_data_td0(:,5));
meansd.m.lat1td10 = mean(meansd.latlongttc1_data_td10(:,1));
meansd.m.ttc1td10 = mean(meansd.latlongttc1_data_td10(:,5));
meansd.m.LO1lowtd0 = mean(meansd.latlongttc1_data_td0(:,2));
meansd.m.LO1medtd0 = mean(meansd.latlongttc1_data_td0(:,3));
meansd.m.LO1hightd0 = mean(meansd.latlongttc1_data_td0(:,4));
meansd.m.LO1lowtd10 = mean(meansd.latlongttc1_data_td10(:,2));
meansd.m.LO1medtd10 = mean(meansd.latlongttc1_data_td10(:,3));
meansd.m.LO1hightd10 = mean(meansd.latlongttc1_data_td10(:,4));
fprintf('Calculating SD...\n');
meansd.sd.ttd0 = (mean(meansd.tBC_data_td0(:,4)-meansd.m.ttd0))/1.645;
meansd.sd.ttd10 = (mean(meansd.tBC_data_td10(:,4)-meansd.m.ttd10))/1.645;
meansd.sd.lat0td0 = (mean(meansd.latttc0_data_td0(:,3)-meansd.m.lat0td0))/1.645;
meansd.sd.ttc0td0 = (mean(meansd.latttc0_data_td0(:,4)-meansd.m.ttc0td0))/1.645;
meansd.sd.lat0td10 = (mean(meansd.latttc0_data_td10(:,3)-meansd.m.lat0td10))/1.645;
meansd.sd.ttc0td10 = (mean(meansd.latttc0_data_td10(:,4)-meansd.m.ttc0td10))/1.645;
meansd.sd.lat1td0 = (mean(meansd.latlongttc1_data_td0(:,6)-meansd.m.lat1td0))/1.645;
meansd.sd.ttc1td0 = (mean(meansd.latlongttc1_data_td0(:,7)-meansd.m.ttc1td0))/1.645;
meansd.sd.lat1td10 = (mean(meansd.latlongttc1_data_td10(:,6)-meansd.m.lat1td10))/1.645;
meansd.sd.ttc1td10 = (mean(meansd.latlongttc1_data_td10(:,7)-meansd.m.ttc1td10))/1.645;

%% Plotting/Printing Results

fprintf('\nPlotting Results\n');
printnominalresults(B.beta,C.beta,C0,C1,B.stats,C.stats,statsC0,statsC1,data,label);

fprintf('\nModell Fitt R² for Non Linear Models (all data)\n');
fprintf('R² of Reaction Times = %5.2f\n',nl_r.Rsquared.Adjusted*100);
fprintf('R² of Take-Over Times = %5.2f\n',nl_t.Rsquared.Adjusted*100);
fprintf('R² of Lateral Accelerations = %5.2f\n',nl_lat.Rsquared.Adjusted*100);
fprintf('R² of Longitudinal Accelerations = %5.2f\n',nl_long.Rsquared.Adjusted*100);
fprintf('R² of TTC = %5.2f\n',nl_ttc.Rsquared.Adjusted*100);

fprintf('\nModell Fitt R² for Non Linear Models (non-braking drivers)\n');
%fprintf('R² of Reaction Times = %5.2f\n',nl_r0.Rsquared.Adjusted*100);
fprintf('R² of Take-Over Times = %5.2f\n',nl_t0.Rsquared.Adjusted*100);
fprintf('R² of Lateral Accelerations = %5.2f\n',nl_lat0.Rsquared.Adjusted*100);
fprintf('R² of TTC = %5.2f\n',nl_ttc0.Rsquared.Adjusted*100);
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fprintf('\nModell Fitt R² for Non Linear Models (braking drivers)\n');
%fprintf('R² of Reaction Times = %5.2f\n',nl_r1.Rsquared.Adjusted*100);
fprintf('R² of Take-Over Times = %5.2f\n',nl_t1.Rsquared.Adjusted*100);
fprintf('R² of Lateral Accelerations = %5.2f\n',nl_lat1.Rsquared.Adjusted*100);
%fprintf('R² of Longitudinal Accelerations = %5.2f\n',nl_long1.Rsquared.Adjusted*100);
fprintf('R² of TTC = %5.2f\n',nl_ttc1.Rsquared.Adjusted*100);

fprintf('\nPercentage of validation data within estimated confidence intervals (all data):\n');
%fprintf('Reaction Time: %7.4f\nTake-Over Time: %7.4f\nLateral Accelerations: %7.4f\nLongitudinal Accelerations: %7.4f\nTime To↙
Collisions: %7.4f\n',withinciper);
%fprintf('\nPercentage of validation data within estimated confidence intervals (non-braking drivers):\n');
%fprintf('Reaction Time: %7.4f\nTake-Over Time: %7.4f\nLateral Accelerations: %7.4f\nLongitudinal Accelerations: %7.4f\nTime To↙
Collisions: %7.4f\n',withinciper0);
%fprintf('\nPercentage of validation data within estimated confidence intervals (braking drivers):\n');
%fprintf('Reaction Time: %7.4f\nTake-Over Time: %7.4f\nLateral Accelerations: %7.4f\nLongitudinal Accelerations: %7.4f\nTime To↙
Collisions: %7.4f\n',withinciper1);

%For the reasons of plotting, data for reaction times must be set to the same length than the other variables, as eor lines are missing.
for i = length(data.in_eor)+1:data.n
    est_r(i) = 0;
    nlme_r.est(i) = 0;
    data.out_eor(i,:) = [0 0 0 0 0];
    est_r_ci(i,:) = [0 0];
end
for i = length(data.in_eor0):data.n0
    %est_r0(i) = 0;
    data.out_eor0(i,:) = [0 0 0 0 0];
    %est_r0_ci(i,:) = [0 0];
end
for i = length(data.in_eor1):data.n1
    %est_r1(i) = 0;
    data.out_eor1(i,:) = [0 0 0 0 0];
    %est_r1_ci(i,:) = [0 0];
end

%For similar reasons, empty confidence intervals for the nominal regressions are generated
est_brake_ci = zeros(data.n,2);
est_brake0_ci = zeros(data.n0,2);
est_brake1_ci = zeros(data.n1,2);
est_crash_ci = zeros(data.n,2);
est_crash0_ci = zeros(data.n0,2);
est_crash1_ci = zeros(data.n1,2);

plot_dataout = data.out;    %Data.out has to be modified for plotting
plot_dataout(:,1)=[];       %Deleting Reaction time responses as data.out_eor is going to be plotted
plot_dataout0 = data.out0;  %Data.out0 has to be modified for plotting
plot_dataout0(:,1)=[];      %Deleting Reaction time responses as data.out0_eor is going to be plotted
plot_dataout0(:,3)=[];      %Deleting brake responses as they are not plotted
plot_dataout1 = data.out1;  %Data.out1 has to be modified for plotting
plot_dataout1(:,1)=[];      %Deleting Reaction time responses as data.out1_eor is going to be plotted
plot_dataout1(:,3)=[];      %Deleting brake responses as they are not plotted

%Plotting brake and crash probability in dependence of brake/crash probability
%Plotting the Graphs
%Graphs for all data
if con.ConsiderCrash == 1;
    plot_capture = {'Estimated Output and Measurement for all data'};
    plot_measured = [data.out_eor(:,1) plot_dataout data.brakesegmented data.crashsegmented];  %Array with measured y-data
    plot_estimated = [est_r est_t est_lat est_long est_ttc B.est(:,2) C.est(:,2)]; %Array with estimated y-data
    plot_ci = [est_r_ci est_t_ci est_lat_ci est_long_ci est_ttc_ci est_brake_ci est_crash_ci];    %Array with confidence bounds
    plot_labels = {'Reaction Time [s]','Take Over Time [s]','Lat. Acc. [m/s²]','Long. Acc. [m/s²]','TTC [s]','Brake Probability [-]','Crash Probability [-↙
]'};    %Array with labels
    plot_x = (0:1:data.n*1-1)'; %X-Values Array with labels
    plot_n = data.n; %Number of trials
    plot_nfigures = 7; %Number of Figures
```

```
    plot_properties = [1 2 4]; %Properties for plotting: [FigNo. Rows Collums]
    plotresults(plot_capture, plot_measured, plot_estimated, plot_ci, plot_x,plot_n, plot_nfigures, plot_labels, plot_properties);

    %Plotting the Graphs NLME-Models
    plot_capture = {'Estimated Output and Measurement for NonLinearMixedEffectModels'};
    plot_measured = [data.out_eor(:,1) plot_dataout data.brakesegmented data.crashsegmented];  %Array with measured y-data
    plot_estimated = [nlme_r.est nlme_t.est nlme_lat.est nlme_long.est nlme_ttc.est B.est(:,2) C.est(:,2)]; %Array with estimated y-data
    plot_ci = [est_r zeros(data.n,1) est_t zeros(data.n,1) est_lat zeros(data.n,1) est_long zeros(data.n,1) est_ttc zeros(data.n,1) B.est(:,2) zeros ↙
(data.n,1) C.est(:,2) zeros(data.n,1)];    %Array with confidence bounds
    plot_labels = {'Reaction Time [s]','Take Over Time [s]','Lat. Acc. [m/s²]','Long. Acc. [m/s²]','TTC [s]','Brake Probability [-]','Crash Probability [-↙
]'};    %Array with labels
    plot_x = (0:1:data.n*1-1)'; %X-Values Array with labels
    plot_n = data.n; %Number of trials
    plot_nfigures = 7; %Number of Figures
    plot_properties = [4 2 4]; %Properties for plotting: [FigNo. Rows Collums]
    plotresults(plot_capture, plot_measured, plot_estimated, plot_ci, plot_x,plot_n, plot_nfigures, plot_labels, plot_properties);
else
    plot_capture = {'Estimated Output and Measurement for all data'};
    plot_measured = [data.out_eor(:,1) plot_dataout data.brakesegmented];  %Array with measured y-data
    plot_estimated = [est_r est_t est_lat est_long est_ttc B.est(:,2)]; %Array with estimated y-data
    plot_ci = [est_r_ci est_t_ci est_lat_ci est_long_ci est_ttc_ci est_brake_ci];    %Array with confidence bounds
    plot_labels = {'Reaction Time [s]','Take Over Time [s]','Lat. Acc. [m/s²]','Long. Acc. [m/s²]','TTC [s]','Brake Probability [-]'};    %Array with↙
labels
    plot_x = (0:1:data.n*1-1)'; %X-Values Array with labels
    plot_n = data.n; %Number of trials
    plot_nfigures = 6; %Number of Figures
    plot_properties = [1 2 4]; %Properties for plotting: [FigNo. Rows Collums]
    plotresults(plot_capture, plot_measured, plot_estimated, plot_ci, plot_x,plot_n, plot_nfigures, plot_labels, plot_properties);

    %Plotting the Graphs NLME-Models
    plot_capture = {'Estimated Output and Measurement for NonLinearMixedEffectModels'};
    plot_measured = [data.out_eor(:,1) plot_dataout data.brakesegmented];  %Array with measured y-data
    plot_estimated = [nlme_r.est nlme_t.est nlme_lat.est nlme_long.est nlme_ttc.est B.est(:,2)]; %Array with estimated y-data
    plot_ci = [est_r zeros(data.n,1) est_t zeros(data.n,1) est_lat zeros(data.n,1) est_long zeros(data.n,1) est_ttc zeros(data.n,1) B.est(:,2) zeros ↙
(data.n,1)];    %Array with confidence bounds
    plot_labels = {'Reaction Time [s]','Take Over Time [s]','Lat. Acc. [m/s²]','Long. Acc. [m/s²]','TTC [s]','Brake Probability [-]'};    %Array with↙
labels
    plot_x = (0:1:data.n*1-1)'; %X-Values Array with labels
    plot_n = data.n; %Number of trials
    plot_nfigures = 6; %Number of Figures
    plot_properties = [4 2 4]; %Properties for plotting: [FigNo. Rows Collums]
    plotresults(plot_capture, plot_measured, plot_estimated, plot_ci, plot_x,plot_n, plot_nfigures, plot_labels, plot_properties);
end

%Graphs for non-braking drivers
plot_capture = {'Estimated Output and Measurement for non-braking drivers'};
plot_measured = [plot_dataout0 data.crash0];  %Array with measured y-data
plot_estimated = [est_t0 est_lat0 est_ttc0 est_crash0(:,2)]; %Array with estimated y-data
plot_ci = [est_t0_ci est_lat0_ci est_ttc0_ci est_crash0_ci];    %Array with confidence bounds
plot_labels = {'Take Over Time [s]','Lat. Acc. [m/s²]','TTC [s]','Accidents [-]'};    %Array with labels
plot_x = (0:1:data.n0*1-1)'; %X-Values Array with labels
plot_n = data.n0; %Number of trials
plot_nfigures = 4; %Number of Figures
plot_properties = [2 2 2]; %Properties for plotting: [FigNo. Rows Collums]
plotresults(plot_capture, plot_measured, plot_estimated, plot_ci, plot_x,plot_n, plot_nfigures, plot_labels, plot_properties);

%Graphs for braking drivers
plot_capture = {'Estimated Output and Measurement for braking drivers'};
plot_measured = [plot_dataout1 data.crash1];  %Array with measured y-data
plot_estimated = [est_t1 est_lat1 est_ttc1 est_crash1(:,2)]; %Array with estimated y-data
plot_ci = [est_t1_ci est_lat1_ci est_ttc1_ci est_crash1_ci];    %Array with confidence bounds
plot_labels = {'Take Over Time [s]','Lat. Acc. [m/s²]','TTC [s]','Accidents [-]'};    %Array with labels
plot_x = (0:1:data.n1*1-1)'; %X-Values Array with labels
plot_n = data.n1; %Number of trials
plot_nfigures = 4; %Number of Figures
```

```
plot_properties = [3 2 2]; %Properties for plotting: [FigNo. Rows Collums]
plotresults(plot_capture, plot_measured, plot_estimated, plot_ci, plot_x,plot_n, plot_nfigures, plot_labels, plot_properties);

%Print Multinomial Regression Results for Lateral and Longitudinal Accelerations
est_ci_zero = zeros(data.n,12);
%plot_dataout(:,2:3)=[];

plot_capture = {'Estimated Output and Measurement for Logistic Lateral and Longitudinal Accelerations'};
plot_measured = [data.latsegmented data.longsegmented];  %Array with measured y-data
plot_estimated = [LA.est LO.est]; %Array with estimated y-data
plot_ci = zeros(data.n,12);    %Array with confidence bounds
plot_labels = {'Lat < 3.5','3.5 < Lat < 7.0','Lat > 7.0','Long > -3.5','-3.5 > Long > -7.0','Long < -7.0'};    %Array with labels
plot_x = (0:1:data.n*1-1)'; %X-Values Array with labels
plot_n = data.n; %Number of trials
plot_nfigures = 6; %Number of Figures
plot_properties = [5 2 3]; %Properties for plotting: [FigNo. Rows Collums]
plotresults(plot_capture, plot_measured, plot_estimated, plot_ci, plot_x,plot_n, plot_nfigures, plot_labels, plot_properties);

plot_capture = {'Estimated Output and Measurement for Logistic Longitudinal Accelerations of Braking Drivers'};
plot_measured = [data.longsegmented1];  %Array with measured y-data
plot_estimated = [LO1.est]; %Array with estimated y-data
plot_ci = zeros(data.n1,6);    %Array with confidence bounds
plot_labels = {'Long > -3.5','-3.5 > Long > -7.0','Long < -7.0'};    %Array with labels
plot_x = (0:1:data.n1*1-1)'; %X-Values Array with labels
plot_n = data.n1; %Number of trials
plot_nfigures = 3; %Number of Figures
plot_properties = [6 1 3]; %Properties for plotting: [FigNo. Rows Collums]
plotresults(plot_capture, plot_measured, plot_estimated, plot_ci, plot_x,plot_n, plot_nfigures, plot_labels, plot_properties);

%Print ROC Curve for Crash
figure(7);
clf;
set(gcf, 'Color', [1,1,1]); %White background
set(gcf, 'Position', [0 0 600 285]); %Size of plot
%Brake ROC
subplot(1,2,1);
[B.roc_x,B.roc_y,B.roc_t,B.roc_auc]=perfcurve(data.brake,B.est(:,2),'1');
plot(B.roc_x,B.roc_y);
xlabel('False positive rate - Brake'); ylabel('True positive rate - Brake');
%Crash ROC
subplot(1,2,2);
[C.roc_x,C.roc_y,C.roc_t,C.roc_auc]=perfcurve(data.crash,C.est(:,2),'1');
plot(C.roc_x,C.roc_y);
xlabel('False positive rate - Crash'); ylabel('True positive rate - Crash');

%Plots for evaluation fit and distribution.
%Please uncomment if needed.
figure(8);
clf;
set(gcf, 'Color', [1,1,1]); %White background
set(gcf, 'Position', [0 0 1050 300]); %Size of plot
set(gca,'FontSize',10); %FontSize
subplot(1,3,1);
%plotResiduals(nl_r, 'probability', 'ResidualType', 'Standardized');
%plotResiduals(nl_r0, 'probability', 'ResidualType', 'Standardized');
%plotResiduals(nl_r1, 'probability', 'ResidualType', 'Standardized');
%plotResiduals(nl_t, 'probability', 'ResidualType', 'Standardized');
plotResiduals(glm_t, 'probability', 'ResidualType', 'Raw');
%plotResiduals(nl_t0, 'probability', 'ResidualType', 'Standardized');
%plotResiduals(nl_t1, 'probability', 'ResidualType', 'Standardized');
%plotResiduals(nl_lat, 'probability', 'ResidualType', 'Standardized');
%plotResiduals(glm_lat, 'probability', 'ResidualType', 'Raw');
%plotResiduals(nl_lat0, 'probability', 'ResidualType', 'Standardized');
%plotResiduals(nl_lat1, 'probability', 'ResidualType', 'Standardized');
%plotResiduals(nl_long, 'probability', 'ResidualType', 'Standardized');
```

```
%plotResiduals(nl_long1, 'probability', 'ResidualType', 'Standardized');
%plotResiduals(nl_ttc, 'probability', 'ResidualType', 'Standardized');
%plotResiduals(glm_ttc, 'probability', 'ResidualType', 'Raw');
%plotResiduals(nl_ttc0, 'probability', 'ResidualType', 'Standardized');
%plotResiduals(nl_ttc1, 'probability', 'ResidualType', 'Standardized');

subplot(1,3,2);
%plotDiagnostics(nl_r, 'cookd');
%plotDiagnostics(nl_r0, 'cookd');
%plotDiagnostics(nl_r1, 'cookd');
%plotDiagnostics(nl_t, 'cookd');
plotDiagnostics(glm_t, 'cookd');
%plotDiagnostics(nl_t0, 'cookd');
%plotDiagnostics(nl_t1, 'cookd');
%plotDiagnostics(nl_lat, 'cookd');
%plotDiagnostics(glm_lat, 'cookd');
%plotDiagnostics(nl_lat0, 'cookd');
%plotDiagnostics(nl_lat1, 'cookd');
%plotDiagnostics(nl_long, 'cookd');
%plotDiagnostics(nl_long1, 'cookd');
%plotDiagnostics(nl_ttc, 'cookd');
%plotDiagnostics(glm_ttc, 'cookd');
%plotDiagnostics(nl_ttc0, 'cookd');
%plotDiagnostics(nl_ttc1, 'cookd');

subplot(1,3,3);
%plotResiduals(nl_r, 'fitted');
%plotResiduals(nl_r0, 'fitted');
%plotResiduals(nl_r1, 'fitted');
%plotResiduals(nl_t, 'fitted');
plotResiduals(glm_t, 'fitted');
%plotResiduals(nl_t0, 'fitted');
%plotResiduals(nl_t1, 'fitted');
%plotResiduals(nl_lat, 'fitted');
%plotResiduals(glm_lat, 'fitted');
%plotResiduals(nl_lat0, 'fitted');
%plotResiduals(nl_lat1, 'fitted');
%plotResiduals(nl_long, 'fitted');
%plotResiduals(nl_long1, 'fitted');
%plotResiduals(nl_ttc, 'fitted');
%plotResiduals(glm_ttc, 'fitted');
%plotResiduals(nl_ttc0, 'fitted');
%plotResiduals(nl_ttc1, 'fitted');

%plot estimated random effects calculated in NLME-models
figure(9);
clf;
set(gcf, 'Color', [1,1,1]); %White background
set(gcf, 'Position', [0 0 1400 300]); %Size of plot
title('Random Effects of NLME');
subplot(1,5,1);
histogram(nlme_r.random);
xlabel('Reaction Time [s]');
ylabel('Quantity [-]');
ylim([0 70]);
subplot(1,5,2);
histogram(nlme_t.random);
xlabel('Take-Over Time [s]');
ylim([0 70]);
subplot(1,5,3);
histogram(nlme_lat.random);
xlabel('Lateral Accelerations [m/s^2]');
ylim([0 70]);
subplot(1,5,4);
histogram(nlme_long.random);
```

```
xlabel('Longitudinal Accelerations [m/s^2]');
ylim([0 70]);
subplot(1,5,5);
histogram(nlme_ttc.random);
xlabel('Time To Collision [s]');
ylim([0 70]);

%Print ROC Curve for Lateral Accelerations
figure(10);
clf;
set(gcf, 'Color', [1,1,1]); %White background
set(gcf, 'Position', [0 0 900 285]); %Size of plot
%Lateral ROC
subplot(1,3,1);
cache = repmat(data.lat_ord,1,3);
for i = 1:3
    cache(:,i) = cache(:,i)-(i-1);
    cache(cache(:,i)~=1,i) = 0;
end
[LA.roc_x1,LA.roc_y1,LA.roc_t1,LA.roc_auc1]=perfcurve(cache(:,1),LA.est(:,1),'1');
[LA.roc_x2,LA.roc_y2,LA.roc_t2,LA.roc_auc2]=perfcurve(cache(:,2),LA.est(:,2),'1');
[LA.roc_x3,LA.roc_y3,LA.roc_t3,LA.roc_auc3]=perfcurve(cache(:,3),LA.est(:,3),'1');
hold on;
plot(LA.roc_x1,LA.roc_y1);
plot(LA.roc_x2,LA.roc_y2);
plot(LA.roc_x3,LA.roc_y3);
legend(['Lat<3.5, AUC=' num2str(LA.roc_auc1,2)],['3.5<Lat<7.0, AUC=' num2str(LA.roc_auc2,2)],['Lat>7.0, AUC=' num2str(LA.roc_auc3,2)]);
xlabel('False positive rate - Lateral'); ylabel('True positive rate - Lateral');

%Longitudinal ROC
subplot(1,3,2);
cache = repmat(data.long_ord,1,3);
for i = 1:3
    cache(:,i) = cache(:,i)-(i-1);
    cache(cache(:,i)~=1,i) = 0;
end
[LO.roc_x1,LO.roc_y1,LO.roc_t1,LO.roc_auc1]=perfcurve(cache(:,1),LO.est(:,1),'1');
[LO.roc_x2,LO.roc_y2,LO.roc_t2,LO.roc_auc2]=perfcurve(cache(:,2),LO.est(:,2),'1');
[LO.roc_x3,LO.roc_y3,LO.roc_t3,LO.roc_auc3]=perfcurve(cache(:,3),LO.est(:,3),'1');
hold on;
plot(LO.roc_x1,LO.roc_y1);
plot(LO.roc_x2,LO.roc_y2);
plot(LO.roc_x3,LO.roc_y3);
legend(['Long>-3.5, AUC=' num2str(LO.roc_auc1,2)],['-3.5>Long>-7.0, AUC=' num2str(LO.roc_auc2,2)],['Long<-7.0, AUC=' num2str(LO.↙
roc_auc3,2)]);
xlabel('False positive rate - Longitudinal'); ylabel('True positive rate - Longitudinal');

%Longitudinal ROC for braking driver
subplot(1,3,3);
cache = repmat(data.long1_ord,1,3);
for i = 1:3
    cache(:,i) = cache(:,i)-(i-1);
    cache(cache(:,i)~=1,i) = 0;
end
[LO1.roc_x1,LO1.roc_y1,LO1.roc_t1,LO1.roc_auc1]=perfcurve(cache(:,1),LO1.est(:,1),'1');
[LO1.roc_x2,LO1.roc_y2,LO1.roc_t2,LO1.roc_auc2]=perfcurve(cache(:,2),LO1.est(:,2),'1');
[LO1.roc_x3,LO1.roc_y3,LO1.roc_t3,LO1.roc_auc3]=perfcurve(cache(:,3),LO1.est(:,3),'1');
hold on;
plot(LO1.roc_x1,LO1.roc_y1);
plot(LO1.roc_x2,LO1.roc_y2);
plot(LO1.roc_x3,LO1.roc_y3);
legend(['Long>-3.5, AUC=' num2str(LO1.roc_auc1,2)],['-3.5>Long>-7.0, AUC=' num2str(LO1.roc_auc2,2)],['Long<-7.0, AUC=' num2str(LO1.↙
roc_auc3,2)]);
xlabel('False positive rate - Longitudinal'); ylabel('True positive rate - Longitudinal');
```

```
%Bringing Validation Data to the same length for plotting
for i = length(val.in_eor)+1:val.n
    val.out_eor(i,:) = [0 0 0 0 0];
    est_val_r_ci(i,:) = [0 0];
    est_val_r(i) = 0;
end
for i = length(val.in0)+1:val.n
    val.out0(i,:) = [0 0 0 0 0];
    est_val_lat0_ci(i,:) = [0 0];
    est_val_ttc0_ci(i,:) = [0 0];
    est_val_lat0(i) = 0;
    est_val_ttc0(i) = 0;
end
for i = length(val.in1)+1:val.n
    val.out1(i,:) = [0 0 0 0 0];
    est_val_lat1_ci(i,:) = [0 0];
    est_val_ttc1_ci(i,:) = [0 0];
    est_val_lat1(i) = 0;
    est_val_ttc1(i) = 0;
end

%Plotting Validation Data
plot_capture = {'Estimated Output and Measurement for Validation Data'};
plot_measured = [val.out_eor(:,1) val.out(:,2) val.out0(:,3) val.out1(:,3) val.out0(:,5) val.out1(:,5)];  %Array with measured y-data
plot_estimated = [est_val_r est_val_t est_val_lat0 est_val_lat1 est_val_ttc0 est_val_ttc1]; %Array with estimated y-data
plot_ci = [est_val_r_ci est_val_t_ci est_val_lat0_ci est_val_lat1_ci est_val_ttc0_ci est_val_ttc1_ci];    %Array with confidence bounds
plot_labels = {'Reaction Time [s]', 'Take Over Time [s]', 'Lat. Acc. Non-Braking [m/s²]', 'Lat. Acc. Braking [m/s²]','TTC Non-Braking [s]', 'TTC↙
Braking [s]'};    %Array with labels
plot_x = (0:1:val.n*1-1)'; %X-Values Array with labels
plot_n = val.n; %Number of trials
plot_nfigures = 6; %Number of Figures
plot_properties = [11 2 3]; %Properties for plotting: [FigNo. Rows Collums]
plotresults(plot_capture, plot_measured, plot_estimated, plot_ci, plot_x,plot_n, plot_nfigures, plot_labels, plot_properties);

%% remove working directory from Matlab's path
for i = 1:length(workingdir)
    rmpath(workingdir{i});
end
```

```
function [data,label,con] = config()
optsr = statset('nlinfit');
optst = statset('nlinfit');
optslat = statset('nlinfit');
optslong = statset('nlinfit');
optsttc = statset('nlinfit');

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% BEGIN OF USER INPUT
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

%Edit to change consideration of crash situations
ConsiderCrash = 1; %0/1

%Multinomial modeling of Lateral and Longitudinal Accelerations?
Multinomial = 1;  %0/1

%Options for Robust Regression
%Fair for Robust Regression, [] for regular regression.
func = 'fair';
%optsr.RobustWgtFun = [];
optsr.RobustWgtFun = func;
%optst.RobustWgtFun = [];
optst.RobustWgtFun = func;
%optslat.RobustWgtFun = [];
optslat.RobustWgtFun = func;
%optslong.RobustWgtFun = [];
optslong.RobustWgtFun = func;
%optsttc.RobustWgtFun = [];
optsttc.RobustWgtFun = func;

%Option to sort the dataset for plotting the results:
sortdata = 0;
%0 = No sorting of dataset
%1 = Sort for TimeBudget and TrafficDensity
%2 = Sort for TimeBudget and Task
%3 = Sort for Column "x"
x = 14;

%Select Validation Data Set
%1 = Thesis; 2 = Lorenz; 3 = Zeeb; 4 = Kerschbaum; 5 = Hergeth
exp = 2;

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% END OF USER INPUT
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

%% Loading the Data

[num,txt] = xlsread('data.xlsx','Tabelle1','A2:X754'); %Read data file
sizedata = size(num); %Measure size of dataset
num = [num rot90(linspace(sizedata(1),1,sizedata(1)))]; %Add a sort variable to the dataset

if sortdata == 1
   num(:,sizedata(2)+1) = num(:,4)./(1+num(:,6))+1./num(:,2);  %Sort algorythm
   num = sortrows(num,sizedata(2)+1); %Sort dataset ascendind
   num = flipud(num); %Flip for descending order
elseif sortdata ==2
   num(:,sizedata(2)+1) = num(:,4).*num(:,8)+1./num(:,2);  %Sort algorythm
   num = sortrows(num,sizedata(2)+1); %Sort dataset ascendind
   num = flipud(num); %Flip for descending order
```

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```
elseif sortdata ==3
    num(:,sizedata(2)+1) = num(:,x);  %Sort algorythm
    num = sortrows(num,sizedata(2)+1); %Sort dataset ascendind
    num = flipud(num); %Flip for descending order
end
crash = num(:,17); %Read crash variable 0/1
if ConsiderCrash == 1
    lines = find(crash<2); %Consider all lines when reading data
else
    lines = find(crash<1); %Consider only lines with no crash wenn reading data
end

eor = num(lines,9); %Read EOR Data
brake = num(lines,16); %Read brake application variable 0/1
didbrake = find(brake>0); %Find lines where participants braked
didntbrake = find(brake<1); %Find lines where participants did not brake

% save output Variables:
out = num(lines,11:15); %Reading output
out0 = out(didntbrake,:);
out1 = out(didbrake,:);

% save input variables
in = num(lines,4:10); %Reading input
in0 = in(didntbrake,:);
in1 = in(didbrake,:);

%save linear data
%linearized input variables, needed for generalized linear model
input_lin_t = [4 5 20 6 21 22 10 23];
in_lin_t = num(lines,input_lin_t);
input_lin_lat = [4 5 6 21 22 10 23];
in_lin_lat = num(lines,input_lin_lat);

% number of datapoints
n = length(out);

% Save Grouping Variable for nlmefit
participant = num(lines,2);
participant0 = participant(didntbrake,:);
participant1 = participant(didbrake,:);

%Ordinal Regression for Lat and Long Accelerations:
% output Variables for multinominal regression braking (ord = ordinal)
lat_ord = double(ordinal(num(lines,13),{'0','1','2'},[],[-0.5,3.5,7.0,12]));
%input_lat = [4 5 6 21 22 8 9 10 23]; %start
input_lat = [4 5 6 21 22 10 23]; %final
in_lat = num(lines,input_lat);

% output Variables for multinominal regression braking (ord = ordinal)
long_ord = double(ordinal(-num(lines,14),{'0','1','2'},[],[-0.5,3.5,7,12]));
long1_ord = long_ord(didbrake,:);
%input_long = [4 5 20 6 21 22 8 9 10 23];%start
input_long = [4 6 22 10 23];%final
in_long = num(lines,input_long);
%input_long1 = [4 6 22];%test
input_long1 = [4 6 8];%final
in_long1 = num(didbrake,input_long1);


% output Variables for multinominal regression braking (ord = ordinal)
brake_ord = double(ordinal(num(lines,16),{'0','1'},[],[-0.5,0.5,1.5]));
crash0 = crash(didntbrake);
crash1 = crash(didbrake);
n0 = length(crash0);
```

```
n1 = length(crash1);

% output Variables for multinominal regression crashes (ord = ordinal)
crash_ord = double(ordinal(num(:,17),{'0','1'},[],[-0.5,0.5,1.5]));
crash_ord0 = crash_ord(didntbrake);
crash_ord1 = crash_ord(didbrake);

% input variables for multinominal regression braking
input_brake = [4 6 22 10 23];
in_brake = num(lines,input_brake);
label_in_brake = {'Itimebudg','Itrafdens','Ireptraining','Iage','Iage2'}; %Label brake explanatory variables
size_in_brake = size(in_brake);
% input variables for multinominal regression crashes
%input_crash = [3 6 21 22 8 9 10 23]; %start
input_crash = [6 21 22]; %final
in_crash = num(:,input_crash);
%label_in_crash = {'Itimebudg','Itrafdens','Itrafdens2','Ireptraining*','ILoad','IEOR','IAge','IAge2'}; %Label crash explanatory variables
label_in_crash = {'Itrafdens','Itrafdens2','Ireptraining*'}; %Label crash explanatory variables
size_in_crash   = size(in_crash);
in_crash0 = in_crash(didntbrake,:);
in_crash1 = in_crash(didbrake,:);


%% Editing and processing the loaded data for reaction time and brake response divided regressions

%Delete crash situations for regression if ConsiderCrash = 0
% Output for eor
eyesoff = find(eor>0); %Read lines of data with eyes off road
%Variables for Reaction Time Regression
out_eor = out(eyesoff,:); %Output for reaction time regression
in_eor = in(eyesoff,:); %Input for reaction time regression
participant_eor = participant(eyesoff,:); %Participant Number for reaction time regression
brake_eor = brake(eyesoff,:); %Brake for reaction time regression

%Sort eor_data for brake application
eor0 = find(brake_eor<1);
eor1 = find(brake_eor>0);

%Data without brake application
out_eor0 = out_eor(eor0,:);
in_eor0 = in_eor(eor0,:);
participant_eor0 = out_eor(eor0,:);

%Data with brake application
out_eor1 = out_eor(eor1,:);
in_eor1 = in_eor(eor1,:);
participant_eor1 = out_eor(eor1,:);


%% Brake / Crash / Lat / Long probability is calculated for segments of 50 measures
%Set number of columns in dependence of considered data
if ConsiderCrash == 1
   rows = 15;
else
   rows = 14;
end
%Average brake (1/0) over 50 measures each
m = mean(reshape(brake(1:rows*50,:), 50, [])); %Average each column
brakesegmented = m(ones(50,1), :); % duplicates vector 50 times
brakesegmented = brakesegmented(:); % vector representation of array using linear indices
remaining = (brakesegmented(rows*50)*50+sum(brake(rows*50:n)))/(n-(rows-1)*50); %Include remaining datapoints
brakesegmented((rows-1)*50:n) = remaining; %Rewrite remaining and last 50 means

%Average crash (1/0) over 50 measures each
m = mean(reshape(crash(1:rows*50,:), 50, [])); %Average each column
```

```
crashsegmented = m(ones(50,1), :); % duplicates vector 50 times
crashsegmented = crashsegmented(:); % vector representation of array using linear indices
remaining = (crashsegmented(rows*50)*50+sum(brake(rows*50:n)))/(n-(rows-1)*50); %Include remaining datapoints
crashsegmented((rows-1)*50:n) = remaining; %Rewrite remaining and last 50 means

%Average Lateral Accelerations (0/1/2) over 50 measures each
latsegmented = zeros(n,3); %latsegmented
longsegmented = zeros(n,3); %longsegmented
longsegmented1 = zeros(n1,3); %longsegmented
for i = 1:3 %Rearrange data to three colums with 0/1
    %Lateral
    cache = lat_ord-(i-1);
    cache(lat_ord~=i) = 0;
    m = mean(reshape(cache(1:rows*50), 50, [])); %Average each column
    segmented = m(ones(50,1),:); % duplicates vector 50 times
    segmented = segmented(:); % vector representation of array using linear indices
    remaining = (segmented(rows*50)*50+sum(cache(rows*50:n)))/(n-(rows-1)*50); %Include remaining datapoints
    segmented((rows-1)*50:n) = remaining; %Rewrite remaining and last 50 means
    latsegmented(:,i) = segmented;

    %Longitudinal
    cache = long_ord-(i-1);
    cache(long_ord~=i) = 0;
    m = mean(reshape(cache(1:rows*50), 50, [])); %Average each column
    segmented = m(ones(50,1), :); % duplicates vector 50 times
    segmented = segmented(:); % vector representation of array using linear indices
    remaining = (segmented(rows*50)*50+sum(cache(rows*50:n)))/(n-(rows-1)*50); %Include remaining datapoints
    segmented((rows-1)*50:n) = remaining; %Rewrite remaining and last 50 means
    longsegmented(:,i) = segmented;

    rows1= 7;
    %Longitudinal braking drivers
    cache = long1_ord-(i-1);
    cache(long1_ord~=i) = 0;
    m = mean(reshape(cache(1:rows1*50), 50, [])); %Average each column
    segmented = m(ones(50,1), :); % duplicates vector 50 times
    segmented = segmented(:); % vector representation of array using linear indices
    remaining = (segmented(rows1*50)*50+sum(cache(rows1*50:n1)))/(n1-(rows1-1)*50); %Include remaining datapoints
    segmented((rows1-1)*50:n1) = remaining; %Rewrite remaining and last 50 means
    longsegmented1(:,i) = segmented;
end

%% construct data struct as function output
data.in = in;
data.out = out;
data.in0 = in0;
data.out0 = out0;
data.in1 = in1;
data.out1 = out1;
data.participant = participant;
data.participant0 = participant0;
data.participant1 = participant1;
data.lat_ord = lat_ord;
data.long_ord = long_ord;
data.long1_ord = long1_ord;
data.in_long = in_long;
data.in_long1 = in_long1;
data.in_lat = in_lat;
data.brake = brake;
data.brake_ord = brake_ord;
data.crash = crash;
data.crash0 = crash0;
data.crash1 = crash1;
data.crash_ord = crash_ord;
data.crash_ord0 = crash_ord0;
```

```
data.crash_ord1 = crash_ord1;
data.n_in_brake = size_in_brake(2);
data.n_in_crash = size_in_crash(2);
data.out_eor = out_eor;
data.in_eor = in_eor;
data.participant_eor = participant_eor;
data.out_eor0 = out_eor0;
data.out_eor1 = out_eor1;
data.in_eor0 = in_eor0;
data.in_eor1 = in_eor1;
data.participant_eor0 = participant_eor0;
data.participant_eor1 = participant_eor1;
data.in_brake = in_brake;
data.in_crash = in_crash;
data.in_crash0 = in_crash0;
data.in_crash1 = in_crash1;
data.n = n;
data.n0 = n0;
data.n1 = n1;
data.crashsegmented = crashsegmented;
data.brakesegmented = brakesegmented;
data.latsegmented = latsegmented;
data.longsegmented = longsegmented;
data.longsegmented1 = longsegmented1;
label.in_brake = label_in_brake;
label.in_crash = label_in_crash;
data.in_lin_t = in_lin_t;
data.in_lin_lat = in_lin_lat;
con.ConsiderCrash = ConsiderCrash;
con.Multinomial = Multinomial;
con.optsr = optsr;
con.optst = optst;
con.optslat = optslat;
con.optslong = optslong;
con.optsttc = optsttc;
con.exp = exp;
```

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```
function [est_nlme, r, r_adj] = estnlme(in, out,var, random_effect, model, k, b, n)
%in = Input variable
%out = dependent variables
%var = selector for selecting the current dependent variable
%random_effect = estimated random effect of nlmefit
%model = regression model
%b = estimated betas
%n = length of dataset

width = size(out); %size of input vektor
out = [out rot90(linspace(n,1,n))]; %add line numbers
in_sorted = sortrows(in,1); %sort input data
out_sorted = sortrows(out,1); %sort output data
out = [out_sorted(:,var+1) out_sorted(:,width(2)+1)]; %select the current dependent variable

j = 0;
selected = 0;

%Assign estimated random effects to dataset
for i = 1:n
   if selected == in_sorted(i,1)
      in_sorted(i,1) = random_effect(j);
   else
      j = j + 1;
      selected = in_sorted(i,1);
      in_sorted(i,1) = random_effect(j);
   end
end

%estimate model output
estimation = model(b, in_sorted(:,2:8));
for i = 1:n
   estimation(i) = estimation(i) + in_sorted(i,1);
end

%calculate residuals
res = out(:,1) - estimation;
%calculate r squared
r = 1-(sum(res.^2)/sum((out(:,1)-mean(out(:,1))).^2));
r_adj = r - (k*(1-r))/(n-k-1);

%resort estimations to original order
estimation = sortrows([estimation out_sorted(:,width(2)+1)],2);

%hand over erstimated model output
est_nlme = estimation(:,1);
```

```
%%Lookup - Table:
%x(:,1) = TimeBudget 5-7.78
%x(:,2) = Lane 1-3
%x(:,3) = TrafficDensity 0-30
%x(:,4) = RepTraining 2-20
%x(:,5) = Workload 0-5
%x(:,6) = EyesOfRoad 0-1
%x(:,7) = Age 19-79

function [model] = models()
%Model Definitions
%-----------------------------------------------------------------------
%Model Reaction Times All
%r.m = @(b,x)(b(1) + b(2)*x(:,1) + b(3)*(log(x(:,4))) + b(4)*x(:,5) + %b(5)*(b(6)+x(:,7)).^2); %start
%r.s = [0.1 0.1 0.1 0.1 0.1 0.1];
%r.k = 4;
r.m = @(b,x)(b(1) + b(2)*x(:,1) + b(3)*x(:,5) + b(4)*(b(5)+x(:,7)).^2); %final
r.s = [0.1 0.1 0.1 0.1 0.1];
r.k = 3;
%r.m = @(b,x)(b(1) + b(2)*x(:,1) + b(3)*x(:,5) + b(4)*x(:,7) + b(5)*x(:,7).^2); %Linearized
%r.s = [0.1 0.1 0.1 0.1 0.1];
%r.k = 4;

%Model Take Over Times All
%t.m = @(b,x)(b(1) + b(2)*x(:,1) + b(3)*(b(4)+x(:,2)).^2 + b(5)*(b(6)+x(:,3)).^2 + b(7)*(log(x(:,4))) + b(8)*x(:,5) + b(9)*x(:,6) + b(10)*(b(11)+x(:,
7)).^2);  %start
%t.s = [0.1 0.1 0.1 0.1 0.1 0.1 0.1 0.1 0.1 0.1 0.1];
%t.k = 7;
t.m = @(b,x)(b(1) + b(2)*x(:,1) + b(3)*(b(4)+x(:,2)).^2 + b(5)*(b(6)+x(:,3)).^2 + b(7)*log(x(:,4))+ b(8)*(b(9)+x(:,7)).^2); %final
t.s = [0.1 0.1 0.1 0.1 0.1 0.1 0.1 0.1 0.1];
t.k = 5;
%t.m = @(b,x)(b(1) + b(2)*x(:,1) + b(3)*x(:,2) + b(4)*x(:,2).^2 + b(5)*x(:,3) + b(6)*x(:,3).^2 + b(7)*x(:,4)+ b(8)*x(:,7) + b(9)*x(:,7).^2);  %
Linearized
%t.s = [0.1 0.1 0.1 0.1 0.1 0.1 0.1 0.1 0.1];
%t.k = 8;

%Model Lateral Accelerations All
%lat.m = @(b,x)(b(1) + b(2)*x(:,1) + b(3)*x(:,2) + b(4)*(b(5)+x(:,3)).^2 + b(6)*(log(x(:,4))) + b(7)*x(:,5) + b(8)*x(:,6) + b(9)*(b(10)+x(:,7)).^2);  %
start
%lat.s = [0.1 0.1 0.1 0.1 0.1 0.1 0.1 0.1 0.1 0.1];
%lat.k = 7;
lat.m = @(b,x)(b(1) + b(2)*x(:,1) + b(3)*x(:,2) + b(4)*(b(5)+x(:,3)).^2 + b(6)*(log(x(:,4))) + b(7)*(b(8)+x(:,7)).^2); %final
lat.s = [0.1 0.1 0.1 0.1 0.1 0.1 0.1 0.1];
lat.k = 5;
%lat.m = @(b,x)(b(1) + b(2)*x(:,1) + b(3)*x(:,2) + b(4)*x(:,3) + b(5)*x(:,3).^2 + b(6)*x(:,4) + b(7)*x(:,7) + b(8)*x(:,7).^2); %Linearized
%lat.s = [0.1 0.1 0.1 0.1 0.1 0.1 0.1 0.1];
%lat.k = 7;

%Model Long. Accelerations All
%long.m = @(b,x)(b(1) + b(2)*x(:,1) + b(3)*(b(4)+x(:,2)).^2 + b(5)*(b(6)+x(:,3)).^2 + b(7)*(log(x(:,4))) + b(8)*x(:,5) + b(9)*x(:,6) + b(10)*(b(11)
+x(:,7)).^2);  %start
%long.s = [0.1 0.1 0.1 0.1 0.1 0.1 0.1 0.1 0.1 0.1 0.1];
%long.k = 7;
%long.m = @(b,x)(b(1) + b(2)*x(:,1) + b(3)*x(:,2) + b(4)*(b(5)+x(:,3)).^2 + b(6)*(log(x(:,4))) + b(7)*x(:,5) + b(8)*x(:,6) + b(9)*(b(10)+x(:,7)).^2);
%start
%long.s = [0.1 0.1 0.1 0.1 0.1 0.1 0.1 0.1 0.1 0.1];
%long.k = 7;
long.m = @(b,x)(b(1) + b(2)*x(:,1) + b(3)*(b(4)+x(:,3)).^2 + b(5)*(log(x(:,4))) + b(6)*(b(7)+x(:,7)).^2); %final
long.s = [0.1 0.1 0.1 0.1 0.1 0.1 0.1];
long.k = 4;
%long.m = @(b,x)(-5.5 +
%6*(((b(1)+b(2)*x(:,1)+b(3)*x(:,4)+b(4)*x(:,5)+b(5)*x(:,6)+b(6)*x(:,8))./((((b(1)+b(2)*x(:,1)+b(3)*x(:,4)+b(4)*x(:,5)+b(5)*x(:,6)+b(6)*x(:,8)).^2+0.5).
^(0.5)))));  %start
%long.s = [0.1 0.1 0.1 0.1 0.1 0.1];
%long.k = 10;
```

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```
%long.m = @(b,x)(b(1) + b(2)*x(:,1) + b(3)*x(:,3) + b(4)*x(:,3).^2 + b(5)*x(:,4) + b(6)*x(:,7) + b(7)*x(:,7).^2); %Linearized
%long.s = [0.1 0.1 0.1 0.1 0.1 0.1 0.1];
%long.k = 6;

%Model TTC All
%ttc.m = @(b,x)(b(1) + b(2)*x(:,1) + b(3)*(b(4)+x(:,2)).^2 + b(5)*(b(6)+x(:,3)).^2 + b(7)*(log(x(:,4))) + b(8)*x(:,5) + b(9)*x(:,6) + b(10)*x(:,7)); %
start
%ttc.s = [0.1 0.1 0.1 0.1 0.1 0.1 0.1 0.1 0.1 0.1];
%ttc.k = 7;
%ttc.m = @(b,x)(b(1) + b(2)*x(:,1) + b(3)*(b(4)+x(:,2)).^2 + b(5)*(b(6)+x(:,3)).^-1 + b(7)*(log(x(:,4))) + b(8)*x(:,5) + b(9)*x(:,7)); %1/x
TrafficDensity
%ttc.s = [0.1 0.1 0.1 0.1 0.1 0.1 0.1 0.1 0.1];
%ttc.k = 6;
ttc.m = @(b,x)(b(1) + b(2)*x(:,1) + b(3)*(b(4)+x(:,2)).^2 + b(5)*(b(6)+x(:,3)).^2 + b(7)*(log(x(:,4))) + b(8)*x(:,5) + b(9)*x(:,7)); %Exponential
TrafficDensity
ttc.s = [0.1 0.1 0.1 0.1 0.1 0.1 0.1 0.1 0.1];
ttc.k = 6;
%ttc.m = @(b,x)(b(1) + b(2)*x(:,1) + b(3)*x(:,2) + b(4)*x(:,2).^2 + b(5)*x(:,3) + b(6)*x(:,3).^2 + b(7)*x(:,4) + b(8)*x(:,5) + b(9)*x(:,7)); %Linearized
%ttc.s = [0.1 0.1 0.1 0.1 0.1 0.1 0.1 0.1 0.1];
%ttc.k = 8;


%Models for non braking drivers
%r0.m = @(b,x)(b(1) + b(2)*x(:,1) + b(3)*(log(x(:,4))) + b(4)*x(:,5) + b(5)*(b(6)+x(:,7)).^2);  %start
%r0.s = [0.1 0.1 0.1 0.1 0.1 0.1];
%r0.k = 4;

%t0.m = @(b,x)(b(1) + b(2)*x(:,1) + b(3)*(b(4)+x(:,2)).^2 + b(5)*(b(6)+x(:,3)).^2 + b(7)*(log(x(:,4))) + b(8)*x(:,5) + b(9)*x(:,6) + b(10)*(b(11)+x(:,
7)).^2);  %start
%t0.s = [0.1 0.1 0.1 0.1 0.1 0.1 0.1 0.1 0.1 0.1 0.1];
%t0.k = 7;
t0.m = @(b,x)(b(1) + b(2)*x(:,1) + b(3)*(b(4)+x(:,2)).^2 + b(5)*(b(6)+x(:,3)).^2 + b(7)*(log(x(:,4))));  %final
t0.s = [0.1 0.1 0.1 0.1 0.1 0.1 0.1];
t0.k = 4;

%lat0.m = @(b,x)(b(1) + b(2)*x(:,1) + b(3)*x(:,2) + b(4)*(b(5)+x(:,3)).^2 + b(6)*(log(x(:,4))) + b(7)*x(:,5) + b(8)*x(:,6) + b(9)*(b(10)+x(:,7)).^2);
%lat0.s = [0.1 0.1 0.1 0.1 0.1 0.1 0.1 0.1 0.1 0.1];
%lat0.k = 7;
lat0.m = @(b,x)(b(1) + b(2)*x(:,1) + b(3)*x(:,2) + b(4)*(b(5)+x(:,3)).^2 + b(6)*(log(x(:,4))) + b(7)*(b(8)+x(:,7)).^2);  %final
lat0.s = [0.1 0.1 0.1 0.1 0.1 0.1 0.1 0.1];
lat0.k = 5;

%ttc0.m = @(b,x)(b(1) + b(2)*x(:,1) + b(3)*(b(4)+x(:,2)).^2 + b(5)*(b(6)+x(:,3)).^2 + b(7)*(log(x(:,4))) + b(8)*x(:,5) + b(9)*x(:,6) + b(10)*x(:,7));
%start
%ttc0.s = [0.1 0.1 0.1 0.1 0.1 0.1 0.1 0.1 0.1 0.1];
%ttc0.k = 7;
ttc0.m = @(b,x)(b(1) + b(2)*x(:,1) + b(3)*(b(4)+x(:,3)).^2 + b(5)*(log(x(:,4))) + b(6)*x(:,5));  %final
ttc0.s = [0.1 0.1 0.1 0.1 0.1 0.1];
ttc0.k = 4;

%Models for braking drivers
%r1.m = @(b,x)(b(1) + b(2)*x(:,1) + b(3)*(log(x(:,4))) + b(4)*x(:,5) + b(5)*(b(6)+x(:,7)).^2);  %start
%r1.s = [0.1 0.1 0.1 0.1 0.1 0.1];
%r1.k = 4;

%t1.m = @(b,x)(b(1) + b(2)*x(:,1) + b(3)*(b(4)+x(:,2)).^2 + b(5)*(b(6)+x(:,3)).^2 + b(7)*(log(x(:,4))) + b(8)*x(:,5) + b(9)*x(:,6) + b(10)*(b(11)+x(:,
7)).^2);  %start
%t1.s = [0.1 0.1 0.1 0.1 0.1 0.1 0.1 0.1 0.1 0.1 0.1];
%t1.k = 7;
t1.m = @(b,x)(b(1) + b(2)*x(:,1) + b(3)*(b(4)+x(:,2)).^2 + b(5)*(b(6)+x(:,3)).^2 + b(7)*(log(x(:,4))) + b(8)*x(:,5) + b(9)*x(:,6));  %final
t1.s = [0.1 0.1 0.1 0.1 0.1 0.1 0.1 0.1 0.1];
t1.k = 6;

%lat1.m = @(b,x)(b(1) + b(2)*x(:,1) + b(3)*x(:,2) + b(4)*(b(5)+x(:,3)).^2 + b(6)*(log(x(:,4))) + b(7)*x(:,5) + b(8)*x(:,6) + b(9)*(b(10)+x(:,7)).^2);
%start
```

```
%lat1.s = [0.1 0.1 0.1 0.1 0.1 0.1 0.1 0.1 0.1 0.1];
%lat1.k = 7;
lat1.m = @(b,x)(b(1) + b(2)*(b(3)+x(:,3)).^2 + b(4)*(b(5)+x(:,7)).^2);  %final
lat1.s = [0.1 0.1 0.1 0.1 0.1];
lat1.k = 2;

%long1.m = @(b,x)(b(1) + b(2)*x(:,1) + b(3)*(b(4)+x(:,2)).^2 + b(5)*(b(6)+x(:,3)).^2 + b(7)*(log(x(:,4))) + b(8)*x(:,5) + b(9)*x(:,6) + b(10)*(b(11)
+x(:,7)).^2);  %start
%long1.s = [0.1 0.1 0.1 0.1 0.1 0.1 0.1 0.1 0.1 0.1 0.1];
%long1.k = 7;

%ttc1.m = @(b,x)(b(1) + b(2)*x(:,1) + b(3)*(b(4)+x(:,2)).^2 + b(5)*(b(6)+x(:,3)).^2 + b(7)*(log(x(:,4))) + b(8)*x(:,5) + b(9)*x(:,6) + b(10)*x(:,7));
%start
%ttc1.s = [0.1 0.1 0.1 0.1 0.1 0.1 0.1 0.1 0.1 0.1];
%ttc1.k = 7;
ttc1.m = @(b,x)(b(1) + b(2)*x(:,1) + b(3)*(b(4)+x(:,2)).^2 + b(5)*(b(6)+x(:,3)).^2 + b(7)*(log(x(:,4))) + b(8)*x(:,5) + b(9)*x(:,7));  %final
ttc1.s = [0.1 0.1 0.1 0.1 0.1 0.1 0.1 0.1 0.1];
ttc1.k = 6;

%% construct data struct as function output
model.r = r;
%model.r0 = r0;
%model.r1 = r1;
model.t = t;
model.t0 = t0;
model.t1 = t1;
model.lat = lat;
model.lat0 = lat0;
model.lat1 = lat1;
model.long = long;
%model.long1 = long1;
model.ttc = ttc;
model.ttc0 = ttc0;
model.ttc1 = ttc1;
```

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```
function [val] = valconfig(exp)

fprintf('Loading validation dataset...\n');
switch exp %Selection of validation experiment
    case 1
        [data,txt] = xlsread('Validierungsdaten.xlsx','Tabelle1','A2:W117');
    case 2
        [data,txt] = xlsread('ValidierungsdatenLorenz14.xlsx','Tabelle1','A2:W44');
    case 3
        [data,txt] = xlsread('ValidierungsdatenZeeb15.xlsx','Tabelle1','A2:W81'); %W90 for Brake estimation
    case 4
        [data,txt] = xlsread('ValidierungsdatenKerschbaum15.xlsx','Tabelle1','A2:W271'); %W271 for TakeOverTime and Lat, 115 for↙
ReactionTime
    case 5
        [data,txt] = xlsread('ValidierungsdatenHergeth16.xlsx','Tabelle1','A2:W221');
end

brake = data(:,15); %Read brake application variable 0/1
didbrake = find(brake>0); %Find lines where participants braked
didntbrake = find(brake<1); %Find lines where participants did not brake
long_ord = double(ordinal(-data(:,13),{'0','1','2'},[],[-0.5,3.5,7,12]));
long1_ord = long_ord(didbrake,:);
input_long1 = [3 5 7];%final
in_long1 = data(didbrake,input_long1);

%All Inputs
in = [data(:,3) data(:,4) data(:,5) data(:,6) data(:,7) data(:,8) data(:,9)];
in0 = in(didntbrake,:);
in1 = in(didbrake,:);
%Inputs needed for brake probability estimation
in_brake = [data(:,3) data(:,5) data(:,21) data(:,9) data(:,22)];
%in_brake = [data(:,3) data(:,5) data(:,6) data(:,7) data(:,9)];
%Inputs needed for crash probability estimation
%in_crash = [data(:,2) data(:,5) data(:,20) data(:,21) data(:,7) data(:,8) data(:,9) data(:,22)];
in_crash = [data(:,5) data(:,20) data(:,21)]; %final
in_crash0 = in_crash(didntbrake,:);
in_crash1 = in_crash(didbrake,:);
%outputs of validation data
out = [data(:,10) data(:,11) data(:,12) data(:,13) data(:,14)];
out0 = out(didntbrake,:);
out1 = out(didbrake,:);
%Brake IO for sorting the validation data to in respect to braking and non braking participants
brake = data(:,15);
%Crasgh IO
crash = data(:,16);
% input variables for multinominal regression braking

%Length of validation data
n = length(data(:,1));

eor = data(:,8); %Read EOR Data
eyesoff = find(eor>0);
out_eor = out(eyesoff,:); %Output for reaction time regression
in_eor = in(eyesoff,:); %Input for reaction time regression

n0 = length(in0);
n1 = length(in1);
n_td0 = length(find(in(:,3)==0));
n_td0_br0 = length(find(in0(:,3)==0));
n_td0_br1 = length(find(in1(:,3)==0));

%% construct data struct as function output

val.n = n;
val.n0 = n0;
```

```
val.n1 = n1;
val.in = in;
val.in_eor = in_eor;
val.in0 = in0;
val.in1 = in1;
val.in_brake = in_brake;
val.in_crash = in_crash;
val.in_crash0 = in_crash0;
val.in_crash1 = in_crash1;
val.out = out;
val.out_eor = out_eor;
val.out0 = out0;
val.out1 = out1;
val.brake = brake;
val.didbrake = didbrake;
val.didntbrake = didntbrake;
val.crash = crash;
val.long1_ord = long1_ord;
val.in_long1 = in_long1;
val.n_td0 = n_td0;
val.n_td0_br0 = n_td0_br0;
val.n_td0_br1 = n_td0_br1;
```

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```
function plotresults(capture, measured, estimated, ci, x, n, nfigures, labels, properties)
% *** function description:
%   * plot input vs time in single/multiple axes
% *** usage:
%   * plotoeminput(pplot,tout,uinp,nu)
% *** input:
%   * pplot      data structure contain plot information (figno,nrow,ncol)
%   * t          time
%   * uinp       input variables
%   * nu         number of input
%   * ulab       input name
% *** output:
%     a plot of input in single/multiple axes
% *** Author and affiliation:
%   * Sembiring, Javensius
%   * Institute of Flight System Dynamics, TUM
% *** created on:
%   * 13 Jun. 2013  - created
% *** revision:
%   * 01 Oct. 2014  - add function description
%   *               - plot in multiple axes defined through pplot
%   * Edited by Christian Gold
%
%% function implemantation

nrow  = properties(2);
ncol  = properties(3);
ci_low = zeros(n,nfigures);
ci_high = zeros(n,nfigures);

k = 0;
for i = 1:nfigures
    ci_low(:,i) = ci(:,k+i);
    ci_high(:,i) = ci(:,k+i+1);
    k = k+1;
end

% *** createa a blank figure, clear if exist
figure(properties(1));
clf;
set(gcf, 'Color', [1,1,1]);
axis([0 800 0 1]);
for k = 1:nfigures
    ax = subplot(nrow,ncol,k);
    set(gcf, 'Position', [0 0 3200 700]);
    plot(x,measured(:,k),'LineWidth',1,'Color',[0.6 0.6 0.6]);
    hold on;
    plot(x,estimated(:,k),'LineWidth',0.5,'Color',[0 0 1]); %Also used for Ordinal Regression
    plot(x,ci_low(:,k),'LineWidth',0.5,'Color',[0.5 0.5 1]);
    %plot(x,ci_low(:,k),'LineWidth',0.25,'Color',[1 0.2 0.2]); %Line inserted for plotting NLME Model
    plot(x,ci_high(:,k),'LineWidth',0.5,'Color',[0.5 0.5 1]);
    %plot(x,measured(:,k),'LineWidth',1.5,'Color',[0 0 0]); %Line inserted for plotting Ordinal Regression
    set(ax,'Box','On');
    ylabel(labels{k});
    xlabel('trial');
end

% *** set legend and figure title
%legend('estimated','measured'); %Line inserted for plotting Ordinal Regression
legend('measured','estimated','ci_{low}','ci_{high}');
%legend('measured','NonLinearMixedEffectModel','NonLinearModel');  %Line inserted for plotting NLME Model
txTitle = suptitle(capture);
set(txTitle,'FontSize',12);
```

```
function printnominalresults(B,C,C0,C1,statsB,statsC,statsC0,statsC1,data,label)
% Print Regression Results for Braking
fprintf('\nResults of Multinominal Regression Braking\n');
fprintf('ln(P(0)/P(1)) = %7.4f ',B(1));
for i = 2:(data.n_in_brake+1)
    fprintf('+ (%7.4f*%13s)',B(i),label.in_brake{i-1});
end
fprintf('\n');
for i = 2:(data.n_in_brake+1)
    fprintf('Stats.p: = %7.4f\n',statsB.p(i));
end
% Print Regression Results for crashes all cases
fprintf('\nResults of Multinominal Regression Crashes - All Cases\n');
fprintf('ln(P(0)/P(1)) = %7.4f ',C(1));
for i = 2:(data.n_in_crash+1)
    fprintf('+ (%7.4f*%13s)',C(i),label.in_crash{i-1});
end
fprintf('\n');
for i = 2:(data.n_in_crash+1)
    fprintf('Stats.p: = %7.4f\n',statsC.p(i));
end
% Print Regression Results for crashes non braking drivers
fprintf('\nResults of Multinominal Regression Crashes - Non-Braking Drivers\n');
fprintf('ln(P(0)/P(1)) = %7.4f ',C0(1));
for i = 2:(data.n_in_crash+1)
    fprintf('+ (%7.4f*%13s)',C0(i),label.in_crash{i-1});
end
fprintf('\n');
for i = 2:(data.n_in_crash+1)
    fprintf('Stats.p: = %7.4f\n',statsC0.p(i));
end
% Print Regression Results for crashes braking drivers
fprintf('\nResults of Multinominal Regression Crashes - Braking Drivers\n');
fprintf('ln(P(0)/P(1)) = %7.4f ',C1(1));
for i = 2:(data.n_in_crash+1)
    fprintf('+ (%7.4f*%13s)',C1(i),label.in_crash{i-1});
end
fprintf('\n');
for i = 2:(data.n_in_crash+1)
    fprintf('Stats.p: = %7.4f\n',statsC1.p(i));
end
```

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```
function [rmse] = valrmse(est, valest, data, valdata)
%r1 = 1 - sum((data-est).^2)/sum((data-mean(data)).^2);
rmse1 = sqrt(sum((data-est).^2)/length(data));

%r2 = 1 - sum((valdata-valest).^2)/sum((valdata-mean(valdata)).^2);
rmse2 = sqrt(sum((valdata-valest).^2)/length(valdata));

%r = r2-r1;
rmse = [rmse1, rmse2, rmse2-rmse1];

end
```

```
function [y,per] = valwithinci(n,estci,out)
% *** function description:
%   * Comparing Confidence Intervals & Validation Data Sets
%   * Checks each line of validation data and all 5 dependent variables if
%   * means are within the confidence interval (->1) or not (->0)

res = zeros(n,1);

for i = 1:n
    if out(i) > estci(i,1) && out(i) < estci(i,2)
        res(i) = 1;
    else
        res(i) = 0;
    end
end

%Calculating Percentage of Values within Confidence Interval
percentage = mean(res);

y = res;
per = percentage;
```