THESIS FOR THE DEGREE OF DOCTOR OF PHILOSOPHY

The driver response process in assisted and automated driving

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Cover:
Two drivers using vehicle automation; an attentive driver in assisted driving (left) and a driver engaged in two non-driving related activities in automated driving (right). These drivers' ability to perform manual driving, when needed, are investigated using the driver response process. The figure shows examples of components included in the driver response process.

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Till Mamma, Pappa, Jenny & Elin
Till Peter & Ted ♥

Abstract

Background: Safe *assisted* and *automated* driving can be achieved through a detailed understanding of the driver response process (the timing and quality of driver actions and visual behavior) triggered by an event such as a take-over request or a safety-relevant event. Importantly, most current evidence on driver response process in vehicle automation, and on automation effects (unsafe response process) is based on driving-simulator studies, whose results may not generalize to the real world. **Objectives:** To improve our understanding of the driver response process 1) in automated driving, which takes full responsibility for the driving task but assumes the driver is available to resume manual control upon request and 2) assisted driving, which supports the driver with longitudinal and lateral control but assumes the driver is responsible for safe driving at all times. **Method:** Data was collected in four experiments on a test track and public roads using the Wizard-of-Oz approach to simulate vehicle automation (assisted or automated). **Results:** The safety of the driver responses was found to depend on the type of vehicle automation. While a notable number of drivers crashed with a conflict object after experiencing highly reliable assisted driving, an automated driving function that issued a take-over request prior to the same event reduced the crash rate to zero. All participants who experienced automated driving were able to respond to the take-over requests and to potential safety-relevant events that occurred after automation deactivation. The responses to the take-over requests consisted of actions such as looking toward the instrument cluster, placing the hands on the steering wheel, deactivating automation, and moving the feet to the pedals. The order and timing of these actions varied among participants. Importantly, it was observed that the driver response process after receiving a take-over request included several off-path glances; in fact, drivers showed reduced visual attention to the forward road (compared to manual driving) for up to 15 s after the take-over request. **Discussion:** Overall, the work in this thesis could not confirm the presence of severe automation effects in terms of delayed response and a degraded intervention performance in safety-relevant events previously observed in driving simulators after automated driving. These differing findings likely stem from a combination of differences in the test environments and in the assumptions about the capabilities of the automated driving system. **Conclusions:** Assisted driving and automated driving should be designed separately: what is unsafe for assisted driving is not necessarily unsafe for automated driving and vice versa. While supervising drivers may crash in safety-relevant events without prior notification during highly reliable assisted driving, a clear and timely take-over request in automated driving ensures that drivers understand their responsibilities of acting in events when back in manual driving. In addition, when take-over requests are issued prior to the event onset, drivers generally perform similar manual driving and intervention performance as in a baseline. However, both before and just after the take-over requests, several drivers directed their gaze mainly off-road. Therefore, it is essential to consider the effect of take-over request designs not only on the time needed to deactivate automation, but also on drivers' visual behavior. Overall, by reporting the results of tests of a future automated driving system (which is in line with future vehicle regulations and insurance company definitions) in realistic environments, this thesis provides novel findings that enhance the picture of automation effects that, before this thesis, seemed more severe.

Keywords: automated driving, driver behavior, driving performance, take-over request, response process, automation safety.

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List of Publications

This PhD thesis includes five journal papers, reported in Table 1. The papers have been published in some of the leading journals in the field of human factors of vehicle automation, and Paper V has been submitted.

Table 1: Appended papers

Papers	
Paper I	**Driver conflict response during supervised automation: Do hands on wheel matter?** **Pipkorn, L.**, Victor, T., Dozza, M., Tivesten, E. (2021). Driver conflict response during supervised automation: do hands on wheel matter? *Transportation Research Part F: Traffic Psychology and Behaviour, 76, 14-25.* https://doi.org/10.1016/j.trf.2020.10.001 ***Author's contribution:*** *The author performed manual video annotation, processed, visualized and analyzed all data, and was the main author of the paper.*
Paper II	**Automation aftereffects: the influence of automation duration, test track and timings** **Pipkorn, L.**, Victor, T., Dozza, M., Tivesten, E. (2022). Automation aftereffects: the influence of automation duration, test track and timings. *IEEE Transactions on Intelligent Transportation Systems, 23(5), 4746-4757.* http://dx.doi.org/10.1109/TITS.2020.3048355 ***Author's contribution:*** *The author took part in designing and piloting the experimental protocol, performed manual video annotation, processed, visualized and analyzed all data, and was the main author of the paper.*
Paper III	**It's about time! Early take-over requests in automated driving enable safer responses to conflicts** **Pipkorn, L.**, Tivesten, E., Dozza, M. (2022). It's about time! Early take-over requests in automated driving enable safer responses to conflicts. *Transportation Research Part F: Traffic Psychology and Behaviour, 86, 196-209.* https://doi.org/10.1016/j.trf.2022.02.014 ***Author's contribution:*** *The author was responsible for designing and piloting the experimental protocol, performed manual video annotation, processed, visualized and analyzed all data, and was the main author of the paper.*
Paper IV	**Driver visual attention before and after take-over requests during automated driving on public roads** **Pipkorn, L.**, Dozza, M., Tivesten, E. (2022). Driver visual attention before and after take-over requests during automated driving on public roads. *Human Factors.* https://doi.org/10.1177/00187208221093863 ***Author's contribution:*** *The author was responsible for designing and piloting the experimental protocol, performed manual video annotation, processed, visualized and analyzed all data, and was the main author of the paper.*
Paper V	**Driver response to take-over requests in real traffic** **Pipkorn, L.**, Tivesten, E., Flannagan., C., Dozza, M. (2022). Driver response to take-over requests in real traffic. *IEEE Transactions on Human-Machine Systems.* Manuscript submitted for publication. ***Author's contribution:*** *The author was responsible for designing and piloting the experimental protocol, performed manual video annotation, processed, visualized and analyzed all data, and was the main author of the paper.*

Contents

1 Introduction

Since its introduction in the late 19th century (Genta et al., 2014), the car has brought many benefits to humanity, such as the possibility to travel long distances without much effort. Driving a car requires precise collaboration between the human and machine. This collaboration works very well most of the time; most drives are uneventful, without damage to vehicle, infrastructure, or passengers (Dingus et al., 2006). However, things can go wrong and crashes with fatal or severely injured occupants are a reality. In fact, about 1.35 million people die in road traffic crashes every year, and tens of millions more suffer from life-altering injuries (World Health Organization [WHO], 2018).

Vehicle automation–technology introduced to automate parts of the driving task in a passenger car–promises to have a positive impact on road safety by reducing the number of road-traffic deaths, since vehicle automation is expected to perform better than a human driver. Thus 94% of the crashes that are related to driver-related critical reasons such as recognition errors, decision errors, and performance errors might be avoided (National Highway Traffic Safety Administration [NHTSA], 2015). However, in order to obtain this safety benefit, vehicle automation needs to be *safe,* resolving the human factors challenges that come with introducing automation into a human-machine system (Bainbridge, 1983; Lee et al., 2017; Lee & Seppelt, 2009; Seppelt & Victor, 2016). Introducing automation may both result in safer driving (e.g., by reducing driver workload; de Winter et al., 2014; Lee et al., 2017), but it may also lead to less safe driving as drivers adapt their behavior to driving with automation instead of pure manual driving (Rudin-Brown, 2010; Rudin-Brown & Parker, 2004), and may therefore not be capable of providing manual control input to, or resuming manual control from, the vehicle automation system when required; Endsley & Kiris, 1995; Bainbridge, 1983).

This thesis examines the safety-critical driver behaviors that may occur when drivers need to perform manual driving after a period of vehicle automation, focusing on two types of vehicle automation, *assisted driving* and *automated driving.* As defined in Thatcham Research (2019), assisted driving refers to vehicle automation systems that assist the driver by performing longitudinal and lateral control (i.e., accelerating, braking and steering the vehicle) when activated; the driver is always responsible for safety despite being assisted with part of the driving task and needs to be prepared to drive manually and respond to objects and events at all times. Thus, the driver needs to be properly engaged in the driving task and typically have eyes on the road and hands on the steering wheel. In contrast, automated driving refers to vehicle automation systems that are assumed to reliably take full responsibility for the driving task when activated, without any need for driver supervision. Thus, the driver is allowed to disengage from the driving task and can take eyes off the road and is not necessarily required to have hands on the steering wheel. However, the driver needs to be ready to resume manual control when the system notifies the driver with a vehicle notification (i.e., a take-over request) when the system meets a situation it is not designed to handle. If the driver does not respond to a take-over request the automated vehicle will need to bring the vehicle to a safe stop (United Nations Economic Commission for Europe [UNECE], 2021).

For the scope of this thesis, examinations of the drivers' ability to start to drive manually either during assisted driving (e.g., the driver needs to steer to avoid a stationary object on the road ahead that is not detected by the system) or after a period of automated driving (e.g., the driver needs to respond to a take-over request, deactivate automation,

and start to drive manually to exit a highway) will be assessed through investigations of the *driver response process* (the timing and quality of driver actions and visual attention) in different scenarios. These scenarios will sometimes include safety-relevant events. Automation effects are present when parts of the driver response process are deemed unsafe (i.e., when the driver response is less safe than what is typical for manual driving). Examples of automation effects are delayed response or a degraded driving performance or crashing in safety-relevant events or a reduced visual attention to the forward roadway. Therefore, to achieve safe vehicle automation, these effects need to be mitigated or prevented.

The majority of evidence on automation effects—particularly, delayed response or crashing in a safety-relevant event—was obtained in driving simulators (Happee et al., 2017; McDonald et al., 2019; Piccinini et al., 2020; Victor et al., 2018). Therefore, one important step towards achieving safe vehicle automation is to understand whether these automation effects generalize to driving a real vehicle on real roads with real motion and visual cues. The test environment may influence our current understanding of automation effects in different ways. First, as several validation studies have failed to reproduce findings from driving simulator studies in real environments, the reported types and size of effects may not apply to real driving conditions (Fisher et al., 2011; Wynne et al., 2019). To use driving simulators successfully, researchers must ensure the cues in the investigation are valid (Kaptein et al., 1996). Examples of cues that play a role for driver response to safety-relevant events are: (a) visual cues to help drivers detect a potential stationary obstacle and understand if it moves or stands still and (b) motion cues to guide driver actions: the actions produced by the car will influence the actions produced by the driver and vice versa (Macadam, 2003). Thus, if visual and motion cues are simulated or even absent observed driver actions may not be real. Finally, automation effects from simulator studies may be misleadingly elevated due to the following reasons: (1) specific types of studies—typically including critical scenarios—are more convenient or only ethically possible in a simulator (de Winter et al., 2021) and (2) the perceived risk is lower in a simulator than in a test track or on-road study (Fisher et al., 2011): as participants know it is a simulation, they may engage in riskier behaviors.

Furthermore, the two automation types (assisted and automated) require more, and individual, attention. To begin with, assisted driving systems in on-market vehicles have already been involved in crashes in real traffic (National Transportation Safety Board [NTSB], 2017, 2018, 2019). A common factor in reports of these crashes is the lack of driver engagement (e.g., long hands-off-wheel times) prior to crashing in safety-relevant events when the assisted driving system did not act to avoid the event. However, the factors (contributing or mitigating) that influenced these crashes are not fully understood. In addition, these factors may not be the same as those in automated driving. At least one car manufacturer has promised their customers a low-speed system in the first half of 2022 (Mercedes-Benz Group, 2021), but on-market vehicles equipped with automated driving systems do not exist on our roads yet. Therefore, the ultimate impact of automated driving on road-traffic safety remains unknown.

In fact, for both automation types (assisted and automated), detailed investigations of the complete driver response process are lacking; most previous studies have assessed the safety of vehicle automation by considering only a single response time (de Winter et al., 2021; McDonald et al., 2019; Zhang et al., 2019). A more complete understanding of the response process is needed because the factors that influence automation effects may not

be apparent otherwise. For example, automation effects may: (a) occur some time after the automated driving system was deactivated and would be missed if only the time needed for drivers to deactivate the system were considered, (b) be influenced by previous actions within the response process (e.g., a delayed response to a safety-relevant event may stem from the time needed to deactivate the system), or (c) be caused by some human mechanism (cognitive or non-cognitive) that can be understood only by detailed investigations of the complete driver response process (e.g., a mechanism that may influence driver steering control only after automation has been deactivated; Mole et al., 2019).

In sum, this PhD thesis is devoted to understanding the driver response process in assisted driving and automated driving, and specifically in which scenarios automation effects are present, the type and size of the effects as well as the factors that contribute to or can mitigate the effects. In turn, understanding details of the driver response process and automation effects can be used to achieve safe vehicle automation by informing the development of, for example, vehicle automation design (e.g., hands-on-wheel requirements, countermeasures), vehicle regulations and consumer rating protocols, and driver models—to be used in computational simulations to estimate the benefit of countermeasures (Bärgman et al., 2017; McDonald et al., 2019) or as reference models in driver monitoring systems (in-vehicle systems that monitor driver states) to counteract unsafe driver behaviors.

1.1 Objectives

The overall aim of this PhD project is to contribute to the development of safe assisted and automated driving, that can be objectively measured. Objectively measured safe assisted and automated driving can be achieved through detailed understanding of the driver response process (including drivers' response to take-over requests in automated driving and the manual driving performance that takes place after automation deactivation and drivers' response to safety-relevant events during assisted driving) and the factors that influence this process. Importantly, there is also a need to advance the ecological validity of the current understanding of the driver response process in assisted and automated driving, that today mainly stems from driving simulator studies, by using data collected in more realistic settings.

To achieve this aim, four objectives were specified:

1. To investigate the driver response process in assisted driving when drivers encounter a safety-relevant event, and specifically the influence of a hands-on-wheel requirement, on a test track.

2. To investigate the driver response process in automated driving when drivers receive a take-over request before encountering a safety-relevant event, and specifically the influence of automation duration, on a test track.

3. To investigate the driver response process in automated driving when drivers receive a take-over request and then encounter the same safety-relevant event as in Objective 1, and specifically the influence of take-over request timings, on a test track.

4. To investigate the driver response process under non-critical conditions in automated driving when drivers receive a take-over request in a naturalistic setting.

2 Background

2.1 Manual driving and event response

Safe manual driving relies on the ability to sense and gather information about the driving environment, attend to and process the relevant information, and respond to the driving situation, both during routine driving and safety-relevant events (Macadam, 2003). The driving task consists of three hierarchical levels of skills and control (Michon, 1985). At the top level (the *strategic* level) the general planning of the trip is executed (e.g., decisions on where to go and how to go there, and whether an automated function should be used). At the middle level (the *tactical* level) decisions are made regarding the maneuvering control related to the present circumstances (e.g., selecting speed, avoiding obstacles, turning, overtaking). Finally, at the lowest level (the *operational level*) the continuous control of the vehicle is performed (e.g., steering, braking, accelerating).

2.1.1 Human detection and response

Humans are naturally programmed to detect and respond to changes in the environment; this ability, vital for our survival, is made possible through the complex interplay between the brain, the spinal cord and the nerves that make up the nervous system (Bear et al., 2001; Spielman et al., 2020).The brain can then influence the activity in the spinal cord to command voluntary movements and produce human action using the muscular system (Bear et al., 2001). Detectable changes in the environment (e.g., light, sound) are typically referred to as stimuli. Specialized neurons called *sensory receptors* respond to different types of stimuli and enable information from the environment to be transmitted to the brain. Importantly, even if a stimuli is strong enough to be detected, we will need some time to respond, as we humans exhibit time delays when responding to stimuli (Macadam, 2003).

Of special importance for the human detection and response in the context of driving is the human visual system as most information relevant for safe driving is gathered using the eyes (Macadam, 2003; Victor et al., 2015). However, not all the sensory information detected by the body is transmitted to the brain; our *attention* guides or selects the information that will be part of higher-level human cognition (Lee et al., 2017). The information we attend to depends on: its salience (e.g., a very loud alarm), the effort needed (e.g., do we need to turn our head), the expectancy of valuable information (e.g., a person is often crossing the road at a certain place) and the value/cost of attending/not attending to a specific stimulus (e.g., if we do not look at the road we may crash). Research suggest that eye movements are closely linked to visual attention, which is specifically related to the human visual system: people tend to direct their gaze to the target of their attention (Hoffman & Subramaniam, 1995; Shinar, 2008). However, the fact that humans look at something does not mean they attend to or perceive it: with *attentional blindness,* a fully visible object is missed because attention was directed somewhere else (Lee et al., 2017). While it is possible to look at something but not attend to it, research suggests that it is not possible to move the eyes to one location while attending to information in another location (Hoffman & Subramaniam, 1995).

2.1.1.1 Frameworks to explain how the brain processes sensory input to produce response

Several frameworks have been developed to illustrate how the brain processes environmental information and produces action. For example, the *information processing model of cognition* represents human information processing as consisting of four stages (Lee et al., 2017; Wickens, 2002). First, we sense the environment; second, we perceive its meaning based on what we sensed (bottom-up processing) and prior knowledge (top-down processing); third, we manipulate the information in our brain either through central processing (e.g., selecting an action) or through transforming and remembering; and fourth, we respond to the information (e.g., by executing the action). All these stages are dependent on a limited pool of attentional resources: if one stage requires a lot of attention, another step may be degraded. This division of information processing into different steps has also been proposed in other models (e.g., Endsley, 1995).

Recently, another framework describing the human cognition and action process in driving has been proposed: *predictive processing,* or PP (Clark, 2013; Engström et al., 2018). It differs from the traditional information-processing assumption of a feed-forward stream of information from sensation to action (e.g., the information processing model of cognition described above). According to the PP framework, the brain continuously predicts sensory input from the external environment (e.g., looming – the visual expansion of an approaching lead vehicle on the retina) and minimizes deviations between predicted and perceived sensory inputs, through action (e.g., braking, steering) or by updating the prediction (Clark, 2013; Engström et al., 2018). The predictions are generated by a hierarchical generative model which is embodied in the brain and develops with experience.

2.2 Vehicle automation

When automation is introduced in a vehicle, the human activities on the operational, tactical, and strategic levels may change. Automation is not necessarily "all or none" but exists to different degrees, often called levels of automation, and these degrees may change the human activities in different ways (Parasuraman et al., 2000). There are several levels of automation, ranging from complete manual control up to full automation when no human input is required (SAE International, 2021; Seppelt & Victor, 2016). Assisted driving generally corresponds to an SAE Level 2 system and automated driving generally corresponds to an SAE Level 4 system (Thatcham Research, 2019). However, a clear one-to-one correspondence does not exist. These two vehicle automation types (assisted and automated) were chosen for this thesis because of the clear distinction in driver roles and responsibilities; the driving is either *shared* when the driver is the one responsible for and in control for safe driving or *delegated* when the vehicle is fully responsible for safe driving (Seppelt & Victor, 2016). Three reasons for such a clear distinction in responsibilities for the driver and the system are: (1) the public confusion about the actual capabilities of current on-market systems (Thatcham Research, 2019); (2) concerns about the expectation that a human is able to provide fallback at any time during automated driving (i.e., to be prepared to act when automation meets a limitation or fails; Seppelt & Victor, 2016); and (3) these definitions (assisted and automated) are being adopted by safety rating organizations and insurance institutes (Euro NCAP, 2018; Thatcham Research, 2019) and will therefore likely guide the design of future vehicle automation systems.

The most mature vehicle automation system on the market today (in 2022) is assisted driving, whereas automated driving systems are currently being developed. For assisted driving, the vehicle can support the drivers with longitudinal and lateral control by combining Adaptive Cruise Control (ACC) with Lane Centering. As noted, the drivers are always responsible for safe driving and are expected to keep their hands on the steering wheel (UNECE, 2017) and their eyes on the road, and to be prepared to respond to conflict objects and events at any time (Seppelt & Victor, 2016; Thatcham Research, 2019). The driver is responsible at all times because of the limitations current systems have which may result in situations that require driver action. For example, vehicle "cut-in" (i.e., another vehicle enters the lane between the subject vehicle and a lead vehicle) and "cut-out" (i.e., another vehicle in front of the subject vehicle leaves the lane to avoid a conflict object on the road) scenarios are challenging for current on-market systems (Euro NCAP, 2021). These types of safety-relevant events frequently occur in everyday traffic, but still surprise drivers, especially when the event requires a fast, precise avoidance maneuver (usually steering and/or braking: Euro NCAP, 2021) to avoid a collision.

An automated driving system, on the other hand, can take full responsibility for the driving task (i.e., longitudinal and lateral control, and event detection and response) for certain periods of time. The system would need to safely handle cut-in- and cut-out scenarios without the need for driver intervention. The driver is not even needed for supervising the system and may disengage from the driving task (hands off the steering wheel and eyes off the road) and engage in non-driving related activities (e.g., using a mobile phone). In fact, a United Nations (UN) vehicle regulation for a future low-speed automated driving system ("Automated Lane Keeping System") is currently being developed by the *Working Party on Automated/autonomous and Connected Vehicles* (GRVA; UNECE, 2021). When the driver has to resume manual control, these systems are required to issue a take-over request (*transition demand* in UNECE, 2021) to notify the driver beforehand for both events known at system activation such as a highway exit (*planned events* in UNECE, 2021) and events unknown at system activation, but assumed likely to happen during driving, e.g., encountering a road-work zone (*unplanned events* in UNECE, 2021). If the driver does not respond to this demand by deactivating automation, the system should start a *minimum risk maneuver* ("a procedure aimed at minimizing risks in traffic, which is automatically performed by the system after a transition demand"; UNECE, 2021) no sooner than 10 s after the transition demand is issued. That is, the vehicle is required to take responsibility for safe driving when the driver is not fit to do so. However, this requirement assumes that systems can detect and notify the driver about an upcoming safety-relevant event more than 10 s beforehand.

2.2.1 Scenarios requiring manual driving and event response in assisted and automated driving

The process of resuming manual control from automated driving is referred to as a *transition* in the UN vehicle regulation (UNECE, 2021) as well as in the ISO 21959 for *human performance and state in the context of automated driving* (ISO, 2020). ISO 21959 presents schematic models for the *transition processes* for both driver-initiated and system-initiated transitions. These models have inspired Figure 1 below, which introduces the terminology used in this thesis in the context of two scenarios: manual driving input

required during assisted driving (Scenario 1) and transition of control from automated driving to manual driving (Scenario 2).

ISO 21959 uses the word *transition* for both assisted driving and automated driving, even though these processes may be fundamentally different. In assisted driving, the driver is responsible for safe driving but is assisted by the system with operational control. This collaboration is shown in Figure 1 (Scenario 1) as the grey bar marked with *driver and assistance system collaborate.* Thus, as the driver is always assumed responsible for driving, a well-defined transition of control does not exist. The driver can either deactivate the system (e.g., by pressing buttons or braking) and drive in manual mode or apply steering wheel torque in order to change the vehicle's path (overriding the function's lane centering by providing manual control input) while the driver assistance system remains active. Importantly, the need for manual control input during assisted driving is not necessarily preceded by a prompt. Even when there is no prompt given by the system, the driver is required to detect and respond to a safety-relevant event that occurs, for example, due to a system limitation (e.g., an unexpected object ahead which the system does not detect, or a steering system torque limitation in a curve). Importantly, *system limitations* should be differentiated from *silent-failure* events, in which the system silently fails in a situation it was designed to handle. In assisted driving, the driver is fully responsible for safe driving at all times and needs to handle events independently if preceded by a prompt or not. In automated driving, the system prompts the driver to resume manual control through a salient notification (i.e., the take-over request) when needed. The take-over request, marked in Figure 1 (TOR; Scenario 2), triggers a *driver state transition:* the "process of transforming the actual driver state (possibly determined by Non-Driving-Related-Activity) to a target driver state suitable to effectively take-over manual control" (ISO, 2020). This transition means that the driver goes from having no responsibility for safe driving to full responsibility for safe driving (see *automation deactivated*; Figure 1).

As shown in the scenarios in Figure 1, the *driver response process* consists of a *response preparation phase*: actions that need to be performed before the driver can start to drive manually (putting hands on the steering wheel, redirecting eyes back on-road) and a *manual intervention and stabilization phase*: the manual intervention and the driving performance that takes place after the driver has started driving manually (i.e., after *start manual intervention*).

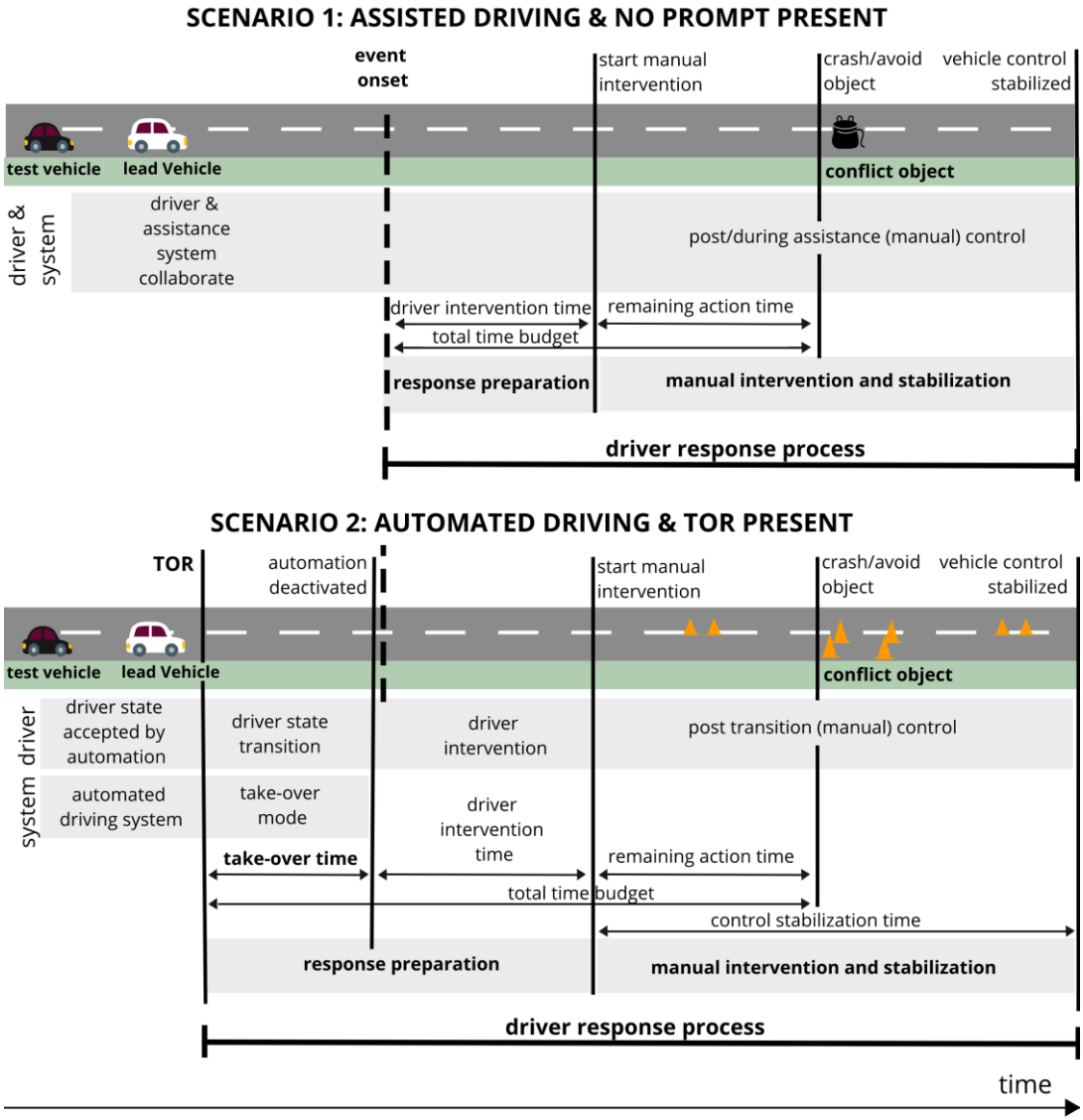

Figure 1 - A representation of the process of driving manually after a period of assisted driving (Scenario 1) and of automated driving (Scenario 2) with a take-over request (TOR) present. The figure defines typical time periods of interest for assessing the driver response process. The two phases making up the complete driver response process (the response preparation phase and the manual intervention and stabilization phase) are marked.

Scenario 1 Description

A test vehicle is following a lead vehicle on a rural road. The test vehicle has the assisted driving system engaged, which means that the driver is responsible for safe driving but is supported by the assisted driving system (driver & assistance system collaborate). Suddenly, a conflict object (garbage bag) becomes briefly visible (event onset) and can be detected by an attentive driver. A little later, the lead vehicle performs a cut-out and fully reveals the conflict object to the driver, who needs to: (a) detect the object and understand the need to act (without being notified by the system), (b) complete the actions in the response preparation phase (e.g., put hands on wheel) in order to be able to start applying steering torque or deactivate the driver assistance system, and (c) steer and/or brake to avoid crashing, since the assisted driving system did not detect it or perform any evasive steering maneuver. In the manual intervention and stabilization phase the driver performs the evasive steering maneuver and then either returns to collaborating with the system or deactivates it and drives without being assisted by the system. Note that the cut-

out scenario is just one example of a system limitation requiring driver control—many others exist (see Euro NCAP, 2021).

Scenario 2 Description

A test vehicle is following a lead vehicle on a rural road. This time, the test vehicle has the automated driving system activated and the driver is engaged in playing a game on his/her tablet with hands off the wheel and eyes off the road. The automated driving system is aware of an upcoming road-work zone (e.g., through receiving the information from another vehicle through vehicle-to-vehicle communication) while the lead vehicle is still blocking the view and notifies the driver to deactivate automation and resume manual control by issuing a take-over request. The driver needs to perform some actions in the response preparation phase such as stopping the game, redirecting his/her eyes from the tablet to the instrument cluster and/or the road, putting his/her hands on the steering wheel, and pressing two buttons in order to deactivate the system. *Automation deactivated* indicates this is achieved. Up ahead, the lead vehicle changes lanes (*event onset*) to avoid colliding with the first part of the road-work zone, two traffic cones (the *conflict objects*). The driver, whose car is now in manual driving mode, needs to start steering (*start manual intervention*), complete the manual intervention and stabilization phase by carefully maneuvering in the road-work zone to avoid colliding with any of the cones, and return to stable manual driving (*vehicle control stabilized* marks when this is achieved). For some systems, the *start manual intervention* may be used to deactivate automation, in which case the *driver intervention time* would be zero. Note that any critical scenarios that could be encountered in manual driving may occur at any time shortly after the driver has resumed manual control.

2.3 Human factors challenges in the context of vehicle automation

Introducing automation into a human-machine system comes with several benefits (Bainbridge, 1983; Lee et al., 2017; Seppelt & Victor, 2016). Benefits of automation over manual operation are increased efficiency and accuracy, as well as the fact that automation can handle tasks that are either dangerous or difficult for humans to handle. However, introducing automation into a human-machine system also comes with costs, that are typically seen when automation is designed in a way that requires human interaction (Seppelt & Victor, 2016). These costs typically stem from the assumption of that a gradual increase in automation will completely eliminate human involvement. However, decades of research on the effects of increasing automation on human performance (mainly in process industries and aviation) tell us that the human tasks and responsibilities are altered rather than eliminated (Bainbridge, 1983; Lee et al., 2017; Seppelt & Victor, 2016). Designers are capable of automating easy tasks, while tasks that are difficult or impossible to automate (or tasks the designers may not be aware of) are left for the human operator to handle. Consequently, the human operator typically becomes responsible for monitoring the automation's performance and resolving scenarios that it is not able to handle. These scenarios often happen unexpectedly, possibly leading to catastrophic outcomes if the human operator is not able to resume manual operation in time. Ironically, the altered task of collaborating with the automated system may be more challenging for the human than manually performing the task in the first place (Bainbridge, 1983). The problem (sometimes referred to as the *out-of-the-loop performance problem*) is that humans working with automation are worse at detecting

system errors and at performing tasks manually when required to than humans who habitually perform the same manual tasks (Endsley & Kiris, 1995). The authors argue that the problem is linked to two major issues with automation: "the loss of manual skills and the loss of awareness of the state and processes of the system". The latter is often referred to as a reduction in *situation awareness* (Endsley, 1995, 2015): "internal conceptualization of the current situation", which occurs on three levels: (1) drivers perceive elements of the environment ("Which information do I need?"), (2) they comprehend the meaning of these elements ("What does this mean to me?"), and (3) they predict the near future ("What do I think will happen next?"). Merat et al. (2018) proposed a definition of *out-of-the-loop* in the context of vehicle automation: "not in physical control of the vehicle and not monitoring the driving situation, OR in physical control of the vehicle but not monitoring the driving situation". In contrast, *in-the-loop* is defined as: "in physical control of the vehicle and monitoring the driving situation" (Merat et al., 2018).

In assisted driving, the driver may not be actively engaged in the driving task on the operational level (longitudinal and lateral control), but is still assumed to be monitoring the system performance and environment and able to quickly provide manual driving input to handle time-critical events without vehicle notification. It is a challenge to ensure that the supervising driver stays in the loop. This challenge stems from one of the *ironies of automation*: the more capable the assisted driving system, the less attention drivers will pay to traffic and the system (e.g., directing less visual attention to the forward road), and the less capable they will be of resuming control (Bainbridge, 1983; Seppelt & Victor, 2016). Certainly, humans are known to be poor at supervising (Warm et al., 2008). Thus, when an assisted driving system performs well without the need for driver input for an extended period of time, there is a risk of reduced monitoring potentially related to some psychological construct such as *overtrust* in the assisted driving system (Parasuraman & Riley, 1997), drivers that are mentally underloaded (Young & Stanton, 2002), or drivers that have insufficient mental models of the automated system (Victor et al., 2018).

Automated driving, in contrast to assisted driving, is designed to allow drivers to be out of the loop, since drivers are free to engage in non-driving related activities and consequently do not need to pay attention to the road or have hands on the steering wheel or feet on the pedals. Thus, the parts of the out-of-the-loop performance problem relevant for automated driving are: (a) the potential loss of manual skills (Lee et al., 2017) as automated driving systems becoming increasingly capable and require less frequent driver input, as the operational design domain is extended (Hi-Drive, 2022) and (b) the need to ensure that the driver will successfully transition from an out-of-the-loop state to an in-the-loop state in response to a take-over request. Furthermore, the success and speed of the drivers response process in automated driving are potentially influenced by some of the previously mentioned psychological constructs, such as drivers that have a reduced situation awareness, are mentally underloaded or have insufficient mental models of the automated system, but could also be due to a less calibrated perceptual-motor control (Mole et al., 2019) or the simple fact that drivers need time to physically return to the position required for manual driving.

Engström et al. (2018) also proposed another explanation for the out-of-the-loop phenomenon in automated driving through the concept of *active inference* and the different levels of the driving task (Michon, 1985). In the context of manual driving, active inference is the continuous minimization of prediction errors by either updating

predictions or acting —on the operational, tactical, or strategic levels—to stay in the loop. However, when automation is introduced, active inference may not take place on the operational or tactical levels, and consequently the driver may be out of the loop. In assisted driving, since the vehicle performs longitudinal and lateral control but the driver still needs to monitor the environment, the driver is assumed to be engaged in perceptual inference rather than active inference on the operational level. This means that the driver may still make predictions about looming by observing a lead vehicle in front. Thus, the driver would still be in the loop on the operational level, even if the type of inference is different from manual driving. However, if drivers monitor the environment without making predictions, they are assumed to be out of the operational loop but may still be engaged in active inference (in the loop) on the tactical and strategic levels. During automated driving, when a driver disengages fully from the driving task and is engaged in an non-driving related activity, the driver may be out of both the tactical and operational control loops.

2.4 State of the art: understanding the driver response process in the context of vehicle automation

A growing amount of researchers is concerned with understanding the scenarios in which drivers may have degraded driving performance—specifically, lowered ability to respond to a safety-relevant event after a period of automated driving, such that parts of the driver response process are unsafe—as well as the factors that influence this ability (Eriksson & Stanton, 2017; McDonald et al., 2019; Mole et al., 2019; Zhang et al., 2019). This section will summarize the state-of-the-art about driver responses in vehicle automation in general, and when the response is unsafe (i.e., automation effects present) specifically. In addition, this section will present typical ways of assessing the driver response process in safety-relevant events in vehicle automation (to determine the presence or absence of automation effects) as well as what is currently known about the influence of specific factors on the response process.

2.4.1 Metrics used to assess the safety of the driver response process

To understand the scenarios in which automation effects are present, as well as the type and size of these effects, means of measuring the driver response process are needed. The driver response to safety-relevant events has traditionally (manual driving or driving with ACC) been examined using reaction times (e.g., driver brake or steering reaction times; Young & Stanton, 2007). A reaction time is typically defined as the duration between the onset of a safety-relevant event (e.g., a lead vehicle that starts to brake) and the start of manual intervention (e.g., the driver brakes). The definition is not always straightforward; for example, in Scenario 1 in Figure 1, the onset of the safety-relevant event could be the time when the conflict object becomes briefly visible the first time or when the lead vehicle performs the cut-out.

Up until now, the most frequently used metric to assess the driver response process in automated driving with a take-over request present is the *take-over time*. The take-over time is the time from when a take-over request is issued to when the driver has deactivated automation (either by a button press or by braking or steering; see Figure 1, Scenario 2). As illustrated in Figure 1, measures of response times (brake response times or take-over times) only capture some aspects of the complete driver response process. For example, the quality of drivers performance in the manual intervention and stabilization phase is

lacking. Recently, it has been proposed that investigations of response times and the response preparation phase need to be combined with analyzes of the manual driving performance that follows a period of assisted or automated driving, because the factors influencing response times may not be the same that influence the driving performance in the manual intervention and performance phase (Figure 1; Mole et al., 2019; Zeeb et al., 2016). Some of these factors may only be understood by considering the drivers' steering behavior after automation (e.g., a less calibrated perceptual-motor control; Mole et al., 2019). However, up until now there has been no well-defined way to assess the success of this phase (McDonald et al., 2019; Mole et al., 2019). Examples of metrics that have been used to assess the driving performance in the manual intervention and stabilization phase are: conflict outcome (crash/no crash), minimum time-to-collision (min TTC), as well as descriptive statistics (mean, maximum, minimum) of longitudinal and lateral accelerations (McDonald et al., 2019).

Another aspect of the driver response process that has not been considered to the same extent as the take-over time or steering/braking response times is the driver's visual behavior. As pointed out in Section 2.1.1, drivers' visual behavior is one of the most significant aspects of safe manual routine driving and event response. Thus, manual driving (after a period of automated driving) and assisted driving both require sufficient levels of visual attention toward the road to be safe. In driving research, drivers' visual attention is typically inferred through measures of eye movements (ISO, 2015; Morando, 2019; Victor, 2005). Common metrics are gaze direction and glance duration. Gaze direction is defined in ISO 15007 as the "area of interest to which the eyes are directed" and glance duration is the "maintaining of visual gaze within an area of interest" (ISO, 2015) for a measured period of time.

To evaluate drivers' visual attention during the response process, some driving simulator studies have included, in addition to take-over time, response times for: (a) redirecting the gaze away from an non-driving related activity item (e.g., Gold et al., 2013), (b) directing the first glance on-road (Eriksson et al., 2018; Gold et al., 2013; Zeeb et al., 2017), and (c) gazing towards mirrors (Gold et al., 2013; Vogelpohl et al., 2018). However, visual response times such as these may overestimate the level of visual attention directed appropriately, since the driver may subsequently glance away. A more comprehensive way of measuring drivers' visual attention during the response process is to compute the PRC (percent road centre: the percentage of time that a driver's gaze is directed on-road over time; Victor et al., 2005) for some specified time interval.

2.4.2 Automation effects and aftereffects: the influence of vehicle automation type on the driver response process

It appears that some of the human factors concerns related to automation in other domains are also present in certain vehicle automation scenarios. Even low degrees of automation (e.g., ACC) have been shown to increase driver brake response times to safety-relevant events when no prompt to the driver is given—compared to manual driving (Larsson et al., 2014; Piccinini et al., 2020; Rudin-Brown & Parker, 2004; Young & Stanton, 2007). Some evidence also indicates that the higher the degree of automation (ACC + Automated steering compared to ACC alone) the poorer the driver response to a safety-relevant event (Strand et al., 2014), but evidence of no effect or minor effects also exists (Larsson et al., 2014; Young & Stanton, 2007). A recent test-track study by Victor et al. (2018) confirmed that drivers may have difficulty responding to a safety-relevant

event similar to that in Scenario 1 during assisted driving. In fact, 28% of the drivers, all reporting high trust in automation to act in the conflict scenario, crashed with the stationary conflict object, which was either a garbage bag or a stationary balloon car. They explained that they did not act, or they acted too late to avoid a crash, because they expected the assisted driving system to avoid the conflict object.

Evidence of *automation aftereffects* (i.e., automation effects specifically occurring after an automated driving system has been deactivated) has also been shown just after an automated driving system was deactivated in response to a take-over request (Gold et al., 2013; Happee et al., 2017; Louw et al., 2015). In addition, some evidence indicates that the longer the *automation duration*, the more severe the automation aftereffects after a take-over request (Bourrelly et al., 2019); however, one other study did not observe any significant automation aftereffects (Feldhütter et al., 2017).

Notably, few studies have directly investigated how the driver response process may differ for assisted driving and automated driving (McDonald et al., 2019). Thus, little is currently known about the similarity of the responses to the same safety-relevant event. The literature gives us reason to be concerned by suggesting that the more we automate, the poorer our ability to perform manual control after automation (Onnasch et al., 2014). However, this observation may not apply to both assisted driving and automated driving, since they differ in whether the drivers receive a take-over request prior to the need to provide manual driving input (assisted driving) or transition to manual driving (automated driving). Notably, warnings given well in advance have been found to elicit earlier responses than late or non-existent warnings (Lee et al., 2002). Thus, comparisons of the driver response processes for assisted driving and automated driving may be influenced both by the vehicle automation type and the presence of a take-over request.

Finally, all studies mentioned in this section were performed in driving simulators, except the study by Victor et al. (2018), performed on a test track. Thus, the question remains to what extent the above findings about automation effects and aftereffects can be reproduced in more realistic contexts (e.g., test track or public road).

2.4.3 Drivers' visual attention and off-road glances during assisted and automated driving

Previous research indicates that automating parts of the driving task may lead drivers to look less on-road than they do during manual driving. For example, previous research reports that PRC is lower during assisted driving than during manual driving on test tracks and in real traffic (Tivesten et al., 2015, 2019). In addition, drivers also tend to exhibit slightly longer off-path glance durations during assisted driving (see Gaspar & Carney, 2019; Morando et al., 2019) than in manual mode. Victor et al. (2018) reported off-path glances of up to 40 s during assisted driving when no attention reminders were given, although drivers were still responsible for supervising the vehicle.

Because automated driving is designed to function without supervision, drivers will likely pay much less attention to the road than they do in manual driving. In line with this hypothesis, a previous driving simulator study reports a significant decrease in PRC from 74.5% in manual driving to 54% during automated driving when the drivers were free to engage in non-driving related activities (Merat et al., 2012). Drivers who are looking away need time after the take-over request to return their visual attention to the road.

Research in driving simulators suggests that drivers typically direct their first glance towards the road within 2 s after the take-over request (Gold et al., 2013; Vogelpohl et al., 2018; Zeeb et al., 2017).

However, as the time from the take-over request to the first on-road glance may overestimate the level of visual attention on road, a more complete way of measuring drivers' visual attention after the take-over request is to compute the PRC for some specified time interval after the take-over request (as previosuly mentioned in Section 2.4.1). Merat et al. (2014) used this method, comparing drivers' PRC one minute after take-over requests issued by automated driving systems, where drivers had to look at the road, using two different strategies. One strategy issued the take-over request every 6 min and another issued the take-over request if drivers looked off path for 10 s or longer. For the take-over request issued at fixed time intervals, drivers' PRC was high (about 70%) 5–10 s after automation deactivation. The PRC then remained at a similar level until 15–20 s had passed. Although the take-over request issued during long off-path glances showed the lowest PRC (58%) 5–10 s after automation deactivation, it increased to 80% when 15–20 s had passed. These results suggest that drivers with long, ongoing off-road glances prior to and at the time of the take-over request need slightly more time to build up to PRC levels of at least 70%.

2.4.4 The influence of specific factors on the driver response process

Many studies have investigated the influence of specific factors on the take-over time, which ranges from 0.7 s up to 23.8 s (Eriksson & Stanton, 2017; Zhang et al., 2019). The take-over time budget (*Total time budget* in Figure 1) is typically defined as the TTC at event onset. This period of time has been pointed out as one of the main factors influencing take-over time: in general, the longer drivers have to resume manual control, the longer they seem to take (McDonald et al., 2019). Additional factors that also influence the take-over time are: whether the transition scenario is practiced beforehand and whether non-driving related activity items (especially hand-held) or prompts are present (McDonald et al., 2019). In fact, it seems that take-over times decrease when there is a prompt (Zhang et al., 2019), but additional work is required to fully understand the influence of prompts on the driver response to safety-relevant events after automation (McDonald et al., 2019).

The review by McDonald et al. (2019) concludes that driving performance in the manual intervention and stabilization phase is significantly influenced by the take-over time budget, non-driving related activity engagement, the modality of the take-over request (e.g., visual, auditory, haptic), the driving environment, presence of a prompt, repeated exposure, fatigue, trust in automation, and alcohol impairment. Many of these factors are the same as the ones influencing the take-over time, perhaps because of the relation between the response preparation phase and the manual intervention and stabilization phase. As the illustrated Scenario 2 in Figure 1 shows, the longer the response preparation phase, the shorter *remaining action time* is available. Consequently, in critical scenarios, drivers may be closer to a conflict object when they act, and therefore either crash or perform a harsh evasive maneuver to avoid crashing. This effect—degraded driving performance as a consequence of the time needed for drivers to prepare to act (by, for example, positioning their hands on the steering wheel)—can be called the *preparation-action-time consequence*. The extent to which the automation aftereffects (Section 2.4.2) may be influenced by the preparation-action-time consequence (a timing

issue) rather than a psychological construct such as reduced situation awareness, is currently unknown.

Whereas factors such as the presence of non-driving related activity items and take-over request modality have received a lot of attention (McDonald et al., 2019), some potentially influential factors have not been focused on to the same extent. One example is a hands-on-wheel requirement (McDonald et al., 2019), which currently exists in Europe for drivers supervising an assisted driving system (UNECE, 2017). At least two studies have explicitly studied the influence of hands-off intervals of either 10 s or 120 s on the driver response process during automated driving when a safety-relevant event was preceded by a take-over request (Naujoks et al., 2015, 2017). Naujoks et al. (2015) found that all drivers responded appropriately (and with similar brake response times) in a longitudinal scenario when encountering a suddenly appearing stationary vehicle for both permitted hands-off durations (10 s vs 120 s). Further, Naujoks et al. (2017) found that drivers responded similarly (independent of the hands-off intervals) in a lateral lane-drift scenario. Notably, both studies mention that most drivers did keep their hands on the steering wheel in both conditions even when they were allowed to take their hands off, which may have explained the similar responses.

Another factor that has received little attention but may influence the driver response process is the type of conflict object used in the safety-relevant events (McDonald et al., 2019). The conflict object type may influence the driver response process because differences in the saliency of different objects may influence their detection (Lee et al., 2017). Finally, drivers' trust in the automated system has been found to influence their response to safety-relevant events during automation: higher trust has been found to result in slower response times and more collisions than lower trust (Körber et al., 2018). More work is still required to fully understand the impact of trust on the driver response process (McDonald et al., 2019).

3 Methods

This chapter gives an overview of the methods, settings, and tools that can be used to study driver behavior in the context of vehicle automation, and specifically the combination of the three that were used to study the driver response process in the five papers included in this thesis (Papers I–V). In addition, this chapter introduces experimental protocols, driving measures, and statistical methods that can be used to assess the driver response process in assisted and automated driving.

3.1 Methods for studying driver behavior and participant selection

Methods for studying driver behavior typically require a compromise between experimental control and realism (McLaughlin et al., 2009). On one side, there are the controlled studies in which two or more independent variables are typically manipulated, and the remaining factors that may influence the measured dependent variable/s are kept fixed. These studies provide an opportunity to study the effect of specific manipulated factors, while ruling out the influence of other factors that vary greatly in a real-world setting but can be precisely controlled in an experimental setting. However, keeping some factors fixed creates an artificial environment which may influence how humans behave, and thus the extent to which the results generalize to real-world settings remains unknown. At the other end of the spectrum are naturalistic studies in which participants are observed in their natural environment with minimum interference. The degree of realism is high, but understanding the relationships between different factors is a challenge because they cannot be controlled.

Examples of test environments for studying driving behavior include driving simulators, test tracks, and public roads (McLaughlin et al., 2009). A driving simulator enables experiments with a high degree of control and the possibility to include critical safety-relevant events without ethical or safety concerns (Fisher et al., 2011). Unfortunately, driving simulators have not been able to reproduce absolute values and sometimes not even absolute differences between conditions: the studies lack absolute validity. However, driving simulators have been able to produce differences in the same direction (e.g., speed reduction) when compared to on-road testing: the studies have relative validity (Fisher et al., 2011). Thus, when absolute values are required (e.g., the actual vehicle speed or accelerations after automation deactivation), tests in more realistic environments, such as test tracks or public roads, are generally necessary. A public-road study can be more or less controlled. An example of a less controlled public-road study is a naturalistic driving study in which drivers use their car (instrumented with sensors) as they normally would in everyday driving (e.g., commuting and shopping) for an extended period of time (weeks or even years). However, a public-road study is more controlled if participants are specifically asked to drive on a certain road segment and to engage in an non-driving related activity. Test-track experiments offers a higher degree of realism than driving simulators, since the visual and kinematic cues are real, but they lack some of the control (McLaughlin et al., 2009). In addition, test-track experiments can be more controlled than public-road studies, since safety-relevant events can be included with higher repeatability and safety compared to tests on public road (even if some ethical restrictions apply to how critical these events can be). Test-track experiments also lack some degree of realism since a test leader and/or a safety driver (serving as a safety back-up) may be present in the car.

The data used in Papers I–III were collected in three test-track experiments which included two safety-relevant events; in a public-road study this design would have been impossible, and in a driving simulator it would have been artificial. Use of a test track enabled the drivers to experience real kinematic feedback from the physical vehicle and the environment, unlike in driving simulators. However, to also understand how drivers interact with systems in a real environment with surrounding traffic and normal driving hazards, the data used in Papers IV–V in this thesis were collected in a public-road experiment.

3.1.1 Participant selection

In order to understand the driver response process and the factors that influence it for assisted and automated driving, human subjects are needed. However, to make statements about a population based on a sample of participants it is important to consider who the selected participants are (e.g., age, gender, education), where they come from (e.g., Sweden, a specific region in Sweden etc.; University of Michigan, 2018), and how they compare to the target population. The participants included in Papers I–V were all Volvo Car employees working in Gothenburg, Sweden. To minimize biases, the participants had no work duties associated with the development of automated driving, did not work as test drivers, and had not been part of similar studies. All participants had driven at least 5000 km during the year prior to the study. All samples were both age- and gender-balanced to the extent possible. All studies included in this thesis were reviewed and approved by the regional ethical review board in Gothenburg (Regionala Etikprövningsnämnden i Göteborg), Sweden (Dnr:369-16, 019–01827).

3.2 Wizard-of-Oz vehicle

While automated driving functions can be easily simulated in a driving simulator, test-track and public-road testing presents a challenge in this regard. Due to the lack of reliable on-market (available for sale) automated vehicles, there is a need to find other ways of investigating human collaboration with vehicle automation. One approach is the *Wizard-of-Oz* technique. In a Wizard-of-Oz experiment (previously *Oz paradigm*), participants think that they are interacting with an automated system, but in reality the automation is simulated by a human who is often partly or fully hidden (Kelley, 2018). When implemented to study interactions between drivers and an automated driving system, the technique enables the vehicle to be controlled from somewhere other than the driver's seat (Habibovic et al., 2016).

The three test-track experiments (Papers I–III) and the public-road experiment (Papers IV and V) used a Wizard-of-Oz vehicle—a Volvo passenger car rebuilt to include a steering wheel and pedals available to a driver (the Wizard) seated in the middle of the back seat. Both the steering wheel and the pedals were hidden from the participant in the driver seat. This setup enabled the Wizard to simulate an automated driving system. The vehicle was equipped with cameras that recorded the forward road, the driver's face, and the driver's upper side body. The public-road experiment also included a camera that recorded driver's foot positions and the vehicle pedals. The vehicle signals collected included speed, longitudinal and lateral acceleration, steering wheel angle, GPS signals, and specific signals capturing when the take-over request was issued and when the driver had deactivated the automated driving system.

3.3 Experimental protocols

Experiments performed to assess the driver response process during assisted driving or after a period of automated driving can be designed in different ways. Typically, the experimental protocols include a period of driving with an assisted or automated driving system engaged, up to a safety-relevant event which requires the drivers to override or deactivate the system and start driving manually to avoid a crash (Gold et al., 2013; Happee et al., 2017; Louw et al., 2015; McDonald et al., 2019). The safety-relevant event can consist of, for example, a braking lead vehicle combined with a silent ACC failure (Piccinini et al., 2020), a cut-in or cut-out scenario (Larsson et al., 2014; Victor et al., 2018), or a conflict object (e.g., a broken-down vehicle) in the lane that drivers need to avoid by steering or braking (Gold et al., 2013; Louw et al., 2015). However, experimental protocols can also investigate drivers' responses to take-over requests under less critical conditions (without an explicit safety-relevant event following the automation deactivation; (Eriksson et al., 2017; Naujoks et al., 2019; Rydström et al., 2022).

The experimental protocols used in Papers I–III included safety-relevant events that required the drivers to act to avoid a crash. In Papers I and III, the event was a cut-out scenario, with a conflict object (either a garbage bag or a stationary vehicle) positioned in the lane (Scenario 1 in Figure 1). In Paper II, the event was a road-work zone made up of cones which was revealed when a lead vehicle changed lanes (Scenario 2 in Figure 1). Papers IV–V investigated the driver response process under non-critical conditions without a safety-relevant event.

3.3.1 The preparation-action time consequence

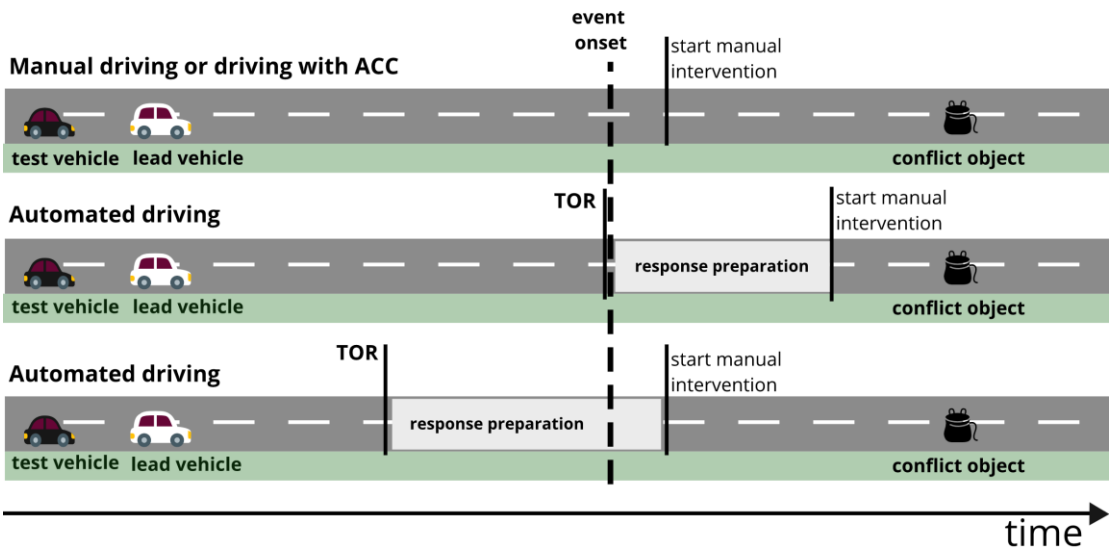

Figure 2 - A representation of how the timings of the take-over request (TOR) and event onset influence the time when drivers start acting to avoid a conflict object as part of a safety-relevant event. The same event is encountered in manual driving or driving with Adaptive Cruise Control (ACC; top row) and automated driving (middle and bottom rows). The middle and bottom rows differ in the timing of the take-over request in relation to the event onset.

When the driver response processes after a period of automated driving and during a baseline drive (typically manual driving) are compared, the timing of the take-over request relative to the event onset is important because of the preparation-action time

consequence (introduced in Chapter 2, Section 2.4.4). Recall that this consequence refers to the automation effects that stem from the time needed for drivers to prepare for action after automation. When the take-over request and the event onset occur at the same time during automated driving (see Figure 2, middle row), the drivers need to complete the actions within the response preparation phase before the *start manual intervention*. In contrast, the drivers in the baseline condition can act directly (assuming they are fully engaged in the driving task). Thus, previous studies that used the setup illustrated in the middle row of Figure 2 may have been biased: the results may have reflected automation aftereffects such as delayed response, degraded manual driving performance, or crashing after automation was deactivated that were simply a consequence of the preparation-action time. In other words, the preparation-action time consequence illustrates how the response preparation phase includes a time delay which does not usually exist when drivers are already in manual driving mode.

In fact, the type of setup used in Papers II–III differed from previous driving-simulator studies (Gold et al., 2013; Happee et al., 2017; Louw et al., 2015), since the take-over request was issued before the event onset (Figure 2, bottom row). This setup enabled the drivers to complete the actions within the response preparation phase before event onset (i.e., before the lead vehicle changed lanes). Paper II included a manual baseline; Paper III, an ACC baseline. Importantly, including a baseline is crucial when searching for automation effects; the manual and ACC baselines included in Paper II-III facilitates an understanding of whether the observed driver behavior (e.g., crashing) is due to the vehicle automation or simply happened because the situation was outside human ability. A very critical safety-relevant event may be unavoidable because humans have time delays when reacting to stimuli, such as a suddenly appearing conflict object (Macadam, 2003).

3.4 Data processing and analysis to assess the safety of the driver response process

As previously mentioned (Chapter 2, Section 2.4.1), the safety of driver responses has mainly been assessed using a single reaction time. However, the driver response to a triggering event can be assessed in more detail by: (a) decomposing reaction times into time components and (b) studying quality of the intervention (brake) profile (Lee et al., 2002). For example, Lee et al. (2002) used this method to study drivers braking behavior in a rear-end collision event. Specifically, they studied the driver response process in more detail by decomposing the brake reaction time (the time from a prompt to the point when the driver began to decelerate) into several components (e.g., accelerator release reaction time and accelerator-to-brake transition time) and assessed the brake profile with the metrics mean and maximum brake accelerations. This method can also be used after a period of assisted or automated driving. Gold et al. (2013) decomposed the take-over time into components such as reaction times for positioning hands on the steering wheel and redirecting eyes to the forward path. Morando et al. (2020), investigating a type of assisted driving that allowed hands off the wheel and feet off the pedals, broke the response process down differently, into its visual components (glance reaction time and the location of that glance), motor components (hands and feet reaction times), and intervention components (time and choice of evasive maneuver). Both Gold et al. (2013) and Morando et al. (2020), in contrast to Lee et al. (2002), included measures of drivers' visual attention as part of the response process. Further, Gold et al. (2013) assessed the manual intervention performance with, for example, lateral vehicle position trajectories

in the safety-relevant event and the utilization of the acceleration potential (i.e., the square-root of the sum of the squared maximum longitudinal and lateral accelerations).

For analyzes of the driver response process, data that capture driver actions (including driver gaze directions) are needed. Some of these data can come from vehicle sensors such as brake pressure or steering wheel torque sensors. However, to capture driver actions that do not involve the vehicle controls (e.g., gaze locations, movement of hands and feet away from the steering wheel or the pedals), video data is typically needed. To collect the data, driving simulators and test cars can be equipped with video cameras that record the driver from different angles (e.g., positioned to capture the driver's face and/or the driver's feet and hands). Then, in order to extract time points for the driver actions of interest, manual video annotation is usually performed: one person (or several people) observes the video and notes the time stamps when a certain action starts (e.g., the driver has at least one hand on the steering wheel). These time stamps can then be extracted and combined into a dataset which can be used to analyze the response process. For analyzes of the intervention and driving performance, a combination of *discrete metrics* (e.g., maximum lateral acceleration, minimum steering wheel angle) and *continuous metrics* (e.g., longitudinal vehicle speed time series data) can be used. In a similar manner, the visual attention can be assessed using discrete metrics (e.g., time until driver gaze is directed on-road in response to a take-over request) or continuous metrics (e.g., the percent of time the gaze is directed towards a certain area of interest over a moving or fixed time window). The risk of only using discrete metrics is that important information can be missed. For example, a discrete difference in lane position observed directly after automation deactivation may simply be a sign that the drivers repositioned their hands on the steering wheel and applied some torque, and not necessarily a safety-critical action. By also including continuous measures of how the lane position changes over time after automation deactivation, a more complete understanding of how meaningful a difference in lane position may be, can be achieved. However, while discrete metrics can easily be included in statistical analyzes to understand effects and effect sizes, continuous metrics may require more advanced methods.

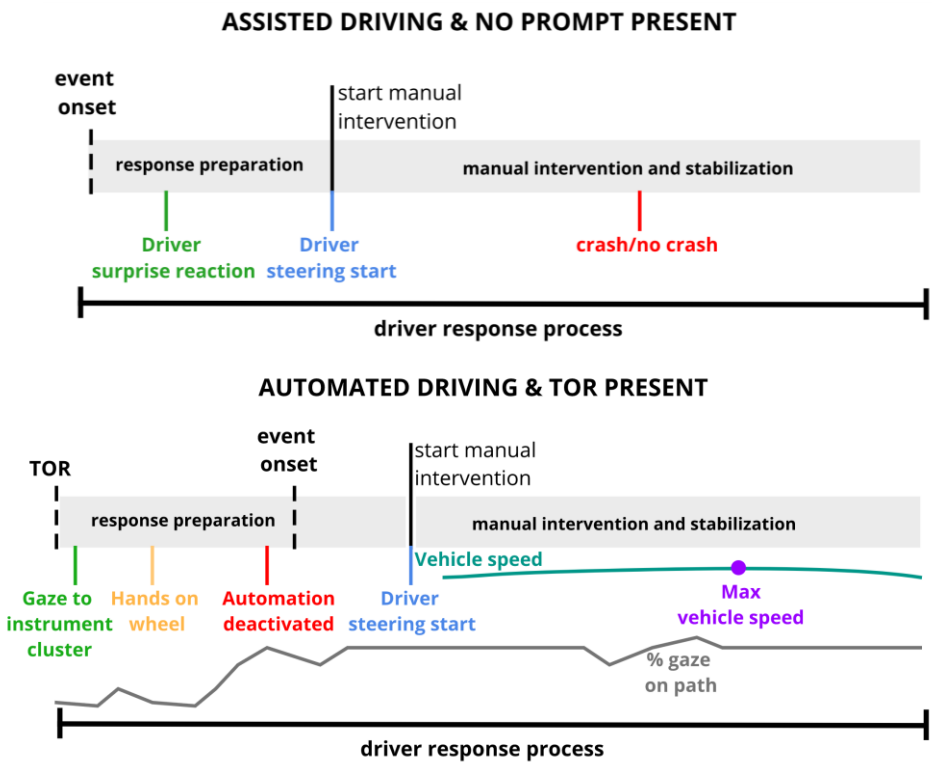

Figure 3 - A representation of the driver response process and the response preparation and the manual intervention and stabilization phases for assisted driving (top) and automated driving (bottom). Included in the figure are examples of the metrics used to capture the timing and quality of the actions within the response process.

Figure 3 presents a subset of Figure 1. The response preparation phase includes all actions that are performed up to the *start manual intervention*, which is typically the point in time when the driver starts to perform a conscious maneuver intended to avoid a safety-relevant event. However, when there is no safety-relevant event, it could be the point in time when the driver starts to provide manual control input. The manual intervention and stabilization phase consists of the manual driving performance that follows after the driver has started driving manually.

The driver response process in Papers I–V was analyzed by performing manual video annotation to extract time points for the specific driver actions (including gaze direction to certain areas, such as the road ahead) of interest. In Papers I–V, the driver response process was assessed using time points for several actions: for example, when a driver showed surprise (Driver Surprise reaction), put hands on wheel (Hands on wheel), started steering to avoid the conflict object (Driver steering start), directed the eyes towards the instrument cluster (Gaze to instrument cluster), and deactivated automation (Automation deactivated). Examples of these time points are shown in Figure 3. These action time points were mainly used to assess the response preparation phase.

In Paper I, the driving performance in the manual intervention and stabilization phase was simply assessed according to the conflict outcome (crash/no crash, indicated in Figure 3). In Papers II and III, the driving performance in the manual intervention and stabilization phases were analyzed in more detail. Vehicle speed and acceleration were

combined with metrics for discrete maximum speed and maximum lateral and longitudinal accelerations, for the period when drivers were maneuvering through the road-work zone (or avoiding the stationary object in the cut-out event). Detailed analyses of driver visual attention, inferred through measures of their gaze direction and glance durations, were conducted, both in the safety-relevant event (Paper I) and before and after a take-over request in automated driving (Paper IV). Specifically, in Paper I the PRC (Figure 3) was computed as a function of time (including several seconds prior to reaching the conflict object) and the values for the drivers who crashed were compared with those who successfully avoided the conflict object. In Paper IV, the percentage gaze directed to areas of interest (e.g., towards the road, an non-driving related activity item, or vehicle mirrors) were analyzed 30 s before and 30 s after the take-over request.

3.4.1 Statistical methods

To mathematically assess the significance of the observed difference between two or more metrics (as part of the driver response process), a variety of statistical methods can be used. Frequentist methods are the most commonly used statistical method within the literature on human factors in vehicle automation. However, frequentist methods (especially null hypothesis significance testing: NHST) have the disadvantage of encouraging black-and-white thinking: effects either exist or do not exist as it mainly indicates whether a *p*-value is rejected or accepted, without explicit information about parameter magnitudes (Kruschke & Liddell, 2018). The real world is often more nuanced, which another type of statistical method, Bayesian, is better at capturing. The output of a Bayesian analysis is a distribution of a parameter together with the uncertainty of this parameter value. Thus, the output includes possible magnitudes as well as probabilities of these magnitudes, making it more informative than NHST. This additional information enables researchers and designers to understand the size of the effect and the uncertainty, and could use that information to assess whether such effect size is meaningful in for them or not in the context they use the information. For example, a difference in vehicle speed may be reported as statistically significant by NHST, but the actual difference in magnitude may be very small (e.g., 0.1 m/s) and not meaningful in every context; a Bayesian analysis enables the reader to make this assessment. The papers included in this PhD thesis used both Frequentist (Papers I and IV) and Bayesian methods (Papers II, III, and V). In Papers II and III, Bayesian methods were used to estimate differences between metrics across conditions (e.g., maximum vehicle speed after automation and after manual driving) together with the uncertainty of this difference. In Paper V, Bayesian methods were used to model the association between the driver response process and a driver's gaze location at the take-over request and repeated exposure to take-over requests, and to predict response times based on a driver's gaze location at the time of the take-over request.

4 Summary of papers

Paper I. Driver conflict response during supervised automation: do hands on wheel matter?

Introduction Understanding how to secure appropriate driver conflict response when needed (e.g., due to system limitations) during assisted driving is an important step in achieving safe vehicle automation. However, in-depth knowledge regarding the mechanisms affecting the driver response process is lacking.

Objective The first aim of this study was to investigate how the driver conflict response in assisted driving differs for drivers who crashed and drivers who avoided the stationary conflict object in a critical event. The second aim was to understand the influence of three factors on the driver response process: a hands-on-wheel requirement (with vs. without), the conflict object type (garbage bag vs. stationary vehicle), and the driver trust level (high vs. low).

Method Seventy-six participants supervised an assisted driving system for 30 minutes on a test track before encountering a conflict event. In the conflict event, the participants needed to avoid a stationary conflict object which was revealed by a lead-vehicle cut-out. The driver conflict response was assessed through investigations of the drivers' response process when they encountered the lead-vehicle cut-out scenario. The process included timepoints for a driver surprise reaction, hands-on-wheel, and driver steering and braking, as well as conflict outcome (crash/no crash).

Results Crashers generally responded later in all the response-process actions compared to non-crashers. A hands-on-wheel requirement did not influence driver conflict response: all drivers started steering to avoid the conflict object at similar times. High-trust drivers generally responded later than the low-trust drivers—or not at all; in fact, only high-trust drivers crashed. The stationary balloon vehicle triggered an earlier surprise reaction than the smaller garbage bag, while the hands-on-wheel requirement and steering response time were similar for the two conflict object types.

Discussion A hands-on-wheel requirement that requires drivers to rest their hands on the steering wheel may not prevent drivers from responding late (or crashing) when drivers have supervised an assisted driving system for 30 minutes. To what extent this result generalizes to other types of conflicts (e.g., sideswipes, lane exits) is currently unknown. In addition, further research is also needed to understand whether a hands-on-wheel requirement that requires a certain amount of torque input would yield different results.

Paper II. Automation aftereffects: the influence of automation duration, test track and timings

Introduction Automation aftereffects—degraded manual driving performance, delayed responses, and more aggressive avoidance maneuvers occurring after automation deactivation—have been observed in driving-simulator studies after a period of automated driving. Further, longer automation duration seems to result in more severe aftereffects than shorter duration.

Objective The aim of this study was to examine the effect of automation exposure and its duration on the response preparation phase and the manual intervention and stabilization phase when drivers encountered a simulated road-work zone on a test track. In addition, comparing the results with those of simulator studies would improve our understanding of the influence of factors such as test environment and experimental protocols on automation aftereffects.

Method Seventeen participants followed a lead vehicle on a test track. They encountered a road-work zone three times: while driving manually and after short and long periods of automated driving. The take-over request was issued 5–6 s before the lead vehicle performed a cut-out and revealed the road-work zone.

Results All drivers managed to resume manual control in response to the take-over request and manoeuvre through the road-work zone with a level of driving performance similar to that of manual driving, without colliding with any cones. The aftereffects of automation on driving performance were greater than the effect of automation duration, but they were minor compared to the aftereffects observed in driving simulator studies.

Discussion The extent to which the difference in automation aftereffects was due to the different test environments (driving simulator vs. test track) or different experimental protocols is unknown. However, independent of test environment, in the search for automation aftereffects it is important to consider the influence of the time needed for the driver response preparation process on the observed aftereffects. That is, more work is needed to disentangle the aftereffects that are merely the result of a longer response-preparation phase (i.e., the preparation-action time) from those that may be caused by some other mechanism or psychological construct (e.g., reduced situation awareness, less calibrated sensorimotor control).

Paper III. It's about time! Earlier take-over requests in automated driving enable safer responses to conflicts

Introduction Automated driving, which takes full responsibility for the driving task in certain conditions, is currently being developed. An important concern in automated driving is how to design a take-over request that mitigates the automation effects—in particular delayed responses to conflict scenarios—that previous literature from simulator experiments has demonstrated.

Objective This study aims to investigate and compare driver responses to take-over requests and a lead-vehicle cut-out scenario under three conditions: (1) after a period of automated driving with a take-over request issued early (18 s time-to-collision), (2) same as (1) except with a take-over request issued late (9 s time-to-collision), and (3) baseline with adaptive cruise control (ACC). This paper also compares these results to those of Paper I, which used the same conflict scenario but with a near-perfect assisted driving system instead.

Method The lead-vehicle cut-out scenario was encountered on a test track after 30 minutes of driving with either ACC or automated driving. In automated driving, the take-over request was issued before the *event onset* (when the lead vehicle performed the cut-out) which revealed the conflict object to the participants. This take-over request strategy differed from previous driving-simulator studies that issued the take-over request at *event onset*. The participants had to respond by steering and/or braking to avoid a crash.

Results Our findings show that, independent of take-over request timing, the drivers required similar amounts of time to 1) direct their first glance to the human–machine interface, 2) look forward, 3) end their non-driving-related activity, 4) put their hands on the steering wheel, and 5) deactivate automation. However, when the take-over request was issued early rather than late, they generally started to brake earlier (even before *event onset*). All participants successfully managed to avoid crashing with the object, independent of the condition. Automated driving with an early take-over request resulted in the earliest response, while ACC drivers responded slightly earlier than the drivers in automated driving with the late take-over request.

Discussion Our findings do not support the findings of severe automation effects reported in previous driving-simulator studies. One reason for the difference is that a take-over request issued prior to event onset gives drivers the time needed for their response-preparation phase. With the extra time, at *event onset* the drivers are ready to act (hands on wheel, eyes forward) and can perform an avoidance maneuver just as in the baseline drive. Overall, this study shows that after a period of automated driving, drivers do not need to end up in a highly critical situation if the take-over request is issued early enough. In fact, automated driving with an early take-over request may be safer than driving with ACC, because in the former drivers are more likely to brake earlier in preparation for the conflict. Finally, a take-over request clearly communicates the need for drivers to resume manual control and handle potential events when the automated driving system has been deactivated. In our study, once the drivers had deactivated automation, they clearly understood their responsibilities to handle the conflict, in contrast to Paper I's near-perfect assisted driving system.

Paper IV. Driver visual attention before and after take-over requests during automated driving on public roads

Introduction Existing research on transitions of control from automated driving to manual driving has mainly focused on take-over times. Despite its relevance for vehicle safety, drivers' visual attention has received little consideration.

Objective This study aims to understand drivers' visual attention before and after take-over requests in automated driving, when the vehicle is fully responsible for the driving task on public roads.

Method Thirty participants took part in a Wizard of Oz study on public roads. Drivers' visual attention was analyzed by measuring gaze direction and glance durations, before and after four take-over requests. Visual attention during a corresponding manual baseline drive was also recorded for comparison.

Results During automated driving, the participants showed less visual attention toward the forward road and longer single off-path glance durations than during manual driving. In response to take-over requests, the participants directed their gaze towards the instrument cluster. Levels of visual attention toward the road did not return to the levels observed during manual driving until 15 s after the take-over request.

Discussion Our findings show the importance of considering the effect of the design of take-over requests on drivers' visual attention alongside take-over times. The reason is that a take-over request may trigger drivers to look away from rather than towards the road; drivers may then deactivate automation before being fully aware of what is happening outside the vehicle. However, our findings may be influenced by the design of the take-over request, which was signaled in the instrument cluster, and may not generalize to other human-machine interface designs.

Work awarded with
The Honda Student Paper
Award at *2021 Driving*
Assessment Conference

Paper V. Driver response to take-over requests in real traffic

Introduction Existing research on transitions of control from automated driving to manual driving mainly consists of studies in virtual settings including a critical event. To understand the impacts of increasing vehicle automation on traffic safety, there is a need for studies conducted on real roads under non-critical conditions.

Objective This study aims to understand how drivers respond to take-over requests in real traffic. Moreover, the study also investigates the association between the drivers' response process and (a) where drivers are looking when they receive the take-over request (towards an non-driving-related activity item or forward) and (b) the repeated exposure to take-over requests.

Method Thirty participants were exposed to four take-over requests after about 5–6 minutes of automated driving (simulated using the Wizard of Oz approach) during a one-hour drive on public roads. While the automated driving system was activated, participants could engage in non-driving related activities of their choice.

Results All drivers responded to the take-over request and deactivated the automated driving system within 10 s of the take-over request. When they received the request, drivers were either looking on-road (38% of requests) or off-road. For the latter, the off-road glance was most commonly towards an non-driving-related activity item. For 72% of the issued take-over requests (independent of drivers' gaze direction at the time), drivers started their response by looking towards the instrument cluster (before placing their hands on the steering wheel and their foot on the accelerator pedal and deactivating automation). Both the timing and the order of these actions varied among participants. In fact, some participants (5%) deactivated automation without having showed a glance forward. The drivers' gaze direction at the time of the take-over request had a stronger association with the response process than the repeated exposure to take-over requests did. A driver who received the take-over request while looking towards an non-driving-related activity item was generally delayed in all parts of the response process, compared to a driver looking on-road at the time of the take-over request.

Discussion As drivers may need several seconds to safely transition from automated driving to manual driving, future automated driving systems must be able to handle the complete driving task for a long time after having issued a take-over request. Driver monitoring systems could be used to support drivers to deactivate automation timely and safely. A driver monitoring system could for example notice whether a driver is engaged in non-driving-related activity s or not, and use that information to decide when to issue a take-over request. Further, driver monitoring systems could also be used to prevent drivers from deactivating the automated driving system before having looked toward the forward roadway.

5 Discussion

5.1 Driver response process during assisted driving

Paper I shows that automation effects may exist when drivers need to act in a lead-vehicle cut-out scenario during assisted driving when no vehicle notification is present. In fact, despite having their eyes on the threat, some drivers responded later in all actions of the response preparation phase of the driver response process, whereas others only showed a surprise reaction without putting their hands on the wheel or attempting to steer. This observed delay in—or lack of—response is in line with previous research on driver conflict response to events with no vehicle notification during driving with some lower degrees of driving assistance, such as ACC or ACC with automated steering (Larsson et al., 2014; Piccinini et al., 2020; Rudin-Brown & Parker, 2004; Strand et al., 2014; Young & Stanton, 2007).

5.1.1 Advantages of the response preparation phase and the influence of a hands-on-wheel requirement

Through its detailed analyzes of the actions within the response preparation phase, Paper I enabled an enhanced understanding of the way these actions were associated with the conflict outcome as previously identified in Victor et al. (2018). In addition, the paper provided insights into how three factors (i.e., a hands-on-wheel requirement, driver trust, and conflict object type) influence driver actions and, consequently, the response process. The paper reported that: (a) some drivers crashed without putting their hands on the steering wheel, whereas others who crashed exhibited a delay in the hands-on-wheel or steering response; (b) high-trust drivers generally put their hands on the wheel and started steering later than low-trust drivers; and (c) a larger conflict object influenced the timing of the surprise reaction, but not that of the hands-on-wheel or steering response. These results build on previous research on driver conflict responses to events without vehicle notification during assisted driving, which mainly focused on the timing of a single response, such as braking (Larsson et al., 2014; Piccinini et al., 2020; Young & Stanton, 2007).

One of the main findings in Paper I was that a hands-on-wheel requirement and supervision reminders during assisted driving did not prevent some drivers from crashing—nor did it elicit an earlier steering response. This finding is in line with previous studies that issued a take-over request prior to a safety-relevant event (Naujoks et al., 2015, 2017), but contrasts with the results of Llaneras et al. (2017), who used a hands-on-wheel requirement that introduced consequences (e.g., need to grab steering wheel, reengage the system) when drivers ignored visual attention reminders in a (silent failure) lane-drift event. Thus, a hands-on-wheel requirement may still be beneficial in other types of conflicts (e.g., lateral lane drifts or incorrect system steering). The extent to which a modified hands-on-wheel requirement in the present study would have been able to mitigate crashing remains unknown. Some sort of hands-on-wheel requirement, inspired by the work of Llaneras et al. (2017), include different types of required physical (hands-on-wheel) involvement which would depend on the drivers' engagement in supervising the assisted driving system. For example, when a driver is examined as insufficiently engaged (and does not change behavior in response to a requirement or reminder): they may first be required to rest their hands on the steering wheel, then to resist the system-

initiated torque, and finally they may need to actively provide steering torque. As these different types of hands-on-wheel involvement represent different degrees of physical control they could potentially be considered different ways of being in the loop according to Merat et al. (2018). To conclude, more work is needed to understand the physical involvement necessary to facilitate a safe and appropriate response to a safety-relevant event during assisted driving when no vehicle notification is present.

5.1.2 Factors explaining delayed response and crashing during assisted driving

Victor et al. (2018) concluded that the drivers who crashed in their study did so because of an *automation expectation mismatch:* they expected the assisted driving feature to avoid the object in the cut-out scenario. This conclusion was based on interviews after the drive, in which drivers reported that they expected the automation to act in the conflict, whereas the participants who avoided a crash reported that they either were uncertain about whether the automation would act or did not expect automation to act at all (Gustavsson et al., 2018; Victor et al., 2018). Paper I confirmed that all drivers showed high levels of visual attention toward the road in the safety-relevant event. In addition, Paper I also found that all drivers except one showed a facial surprise reaction in the safety-relevant event. This sign of surprise may be an indication that the drivers were aware of the conflict object.

In addition, Paper I found that drivers who reported high trust in automation responded later than drivers who reported low trust in automation. The predictive processing (PP) framework (Clark, 2013) was proposed as a possible explanation for the difference. Explaining the results within the PP framework was novel: despite the recent advances of PP within cognitive neuroscience, this framework is rarely used to explain results in the literature on human factors in vehicle automation. Simply put, the delayed response and consequent crashing reported in Paper I may arise from the participants who crashed have a different understanding of the assisted driving systems' capabilities than the ones who avoided crashing. In the PP framework, this difference in understanding can be explained as crashing and avoiding participants having different hierarchical generative models. Further, the difference in responses by the high-trust drivers who crashed and the ones who did not may arise from the drivers' different involvement in the driving task on the operational level (Michon, 1985). In the PP framework, this can be explained as the high-trust drivers who avoided a crash was involved in perceptual inference (they were making predictions on looming) on the operational level, whereas the crashing high-trust drivers were not engaged in any inference on the operational level. Other frameworks or conceptual models may also be useful to explain the results, but these were not considered within the scope of this thesis.

5.2 Driver response process after a period of automated driving on a test track

In contrast to Paper I, which focused on the driver response process during assisted driving, Papers II–V investigated the process after a period of automated driving. The work in these papers provides novel contributions to the literature on human factors in vehicle automation, which consists almost entirely of evidence from virtual environments. These papers, however, are based on data collected in more realistic test

environments, such as a test track and public roads, using a physical vehicle. As a result, the data presented in Papers II–V are more reliable and representative of driver and vehicle behavior, within the typical limitations of an experimental setup.

5.2.1 Driver response to safety-relevant events on test track

The finding of automation effects in Paper I, which combined assisted driving with a unexpected system-limitation event, motivated the work in Papers II and III. Generally, these papers were aimed at understanding whether the type of automation effects observed for assisted driving can be generalized to driving with an automated driving system that issues a take-over request prior to the need for manual driving. First, Paper II aimed to understand if automation effects would also be present in another safety-relevant event that was assumed to be easier for the drivers to handle than the cut-out event investigated in Paper I. The question was addressed in Paper II by letting drivers encounter a simulated roadwork after a period of automated driving that was previously encountered during a manual baseline (i.e., the event was expected and practiced beforehand). In contrast, the cut-out event in Paper I was unexpected; the drivers only encountered the event once. Paper III investigated whether automation effects would be present in the same scenario as in Paper I —for an automated driving system that issued a take-over request well in advance of the conflict object.

Interestingly, despite the increased automation and the fact that all drivers in Paper II (instructed non-driving-related activity engagement) and some drivers in Paper III (voluntary non-driving-related activity engagement) were out of the loop before the take-over request, only minor automation aftereffects were observed. All drivers, after having deactivated the automated driving system, started their steering maneuver earlier or at approximately the same time as in the baseline condition (manual in Paper II, ACC in Paper III); further, they showed similar driving performances in the safety-relevant event. The extent to which the difference in automation effects between Paper I and II depend on the criticality and expectancy of different safety-relevant events, type of automation, and presence of a vehicle notification is unclear. However, the fact that Paper III included the same safety-relevant event as in Paper I suggests that the explanation lies in the different automation types (assisted vs. automated) which includes the presence or absence of a take-over request, rather than in the type of safety-relevant event. Importantly, we could not confirm the human factors assumption of that increased automation typically results in poorer performance (Onnasch et al., 2014). However, this assumption does not apply to systems that also differ in their ability to provide timely notifications to the human operator. In fact, vehicle notifications that attract drivers' attention have been found to decrease response times (Lee et al., 2002), and the presence of a take-over request in Papers II and III (unlike Paper I) is likely to explain an important part of the appropriate responses observed.

It also seems that, if a take-over request is triggered with sufficient time before event onset, the drivers are able to re-engage in the driving task on both the operational and tactical levels (Michon, 1985) and start making predictions about looming (as assumed by the PP framework) in a timely manner, avoiding crashing in the safety-relevant event. According to the PP framework, the fact that the drivers responded in time shows that they generated prediction errors to be acted upon (Clark, 2013; Engström et al., 2018). It can be assumed that the drivers were not making predictions about looming during automated driving (in Paper II they were looking at the game they were playing; in Paper

III at some other non-driving related activity item). Therefore, these drivers must have had sufficient time after the take-over request to start making predictions about looming (re-engage in active inference on operational level) in order to generate the prediction errors they acted upon.

5.2.1.1 Factors explaining automation effects when responding to take-over requests in automated driving

The minor automation aftereffects in Papers II and III, in contrast to the significant aftereffects in previous studies in driving simulators (Gold et al., 2013; Happee et al., 2017; Louw et al., 2015), may be explained by several factors. One such factor is that the data included in Papers II-III was collected on real roads with a real vehicle with presence of real visual and motion cues and force feedback. Specifically, the absence of real motion cues and force feedback in previous driving simulator studies may have influenced the size of the accelerations generated to avoid a crash after automation deactivation. Both Gold et al. (2013) and Louw et al. (2015) report an increase in generated accelerations after automation compared to the manual baseline that was notably higher than what was observed in Papers II and III. However, to really understand the influence of test environment on the difference in observed automation aftereffects a validation study of the specific driving simulator is required (Kaptein et al., 1996). Another factor that may influence observed differences in aftereffects across studies is that Papers II and III differed in terms of test environment and automated system specifications from the "typical" driving-simulator setup used in previous research. This setup let participants drive with an automated driving system on a highway at high speeds (120 km/h) before encountering a safety-relevant event (often a crash scene with stationary vehicles; de Winter et al., 2021). When the safety-relevant event became visible to the automated driving system it issued a take-over request; if the driver did not respond within the typical time budget of 7 s (or less) a crash would occur. The drivers could simultaneously deactivate the automated driving system and act to avoid the collision by simply steering or braking. Further, the automated driving system was assumed to be capable of issuing take-over requests for planned and unplanned events including objects that were not necessarily visible to the vehicle's radar (i.e., before event onset) and then typically at longer time budgets (about 10 s or more). In addition, the automated driving system included a deactivation strategy that grants insurance companies' wish for a clear distinction between the responsibilities of the human and the vehicle in the driving task, since drivers had to press and hold two buttons on the steering wheel for about 0.6 s to transition from automated driving to manual driving or vice versa.

Given these differences in automated driving system designs, one reason why the findings in Papers II and III differ from those in previous driving-simulator studies is the *preparation-action-time consequence* (introduced in Sections 2.4.4 and 3.3.1). In sum, the less severe automation aftereffects may be due to the fact that the drivers in those studies had time to resume manual control before being presented with the conflict object because the take-over request was issued prior to event onset. In other words, after a period of automated driving, the automation aftereffects—in particular delayed response, degraded driving performance, and crashing—may be the result of the time it takes after automation for drivers to prepare for action (e.g., repositioning hands on the steering wheel). However, automation aftereffects may also be the result of any of the psychological constructs mentioned in Chapter 2, Section 2.3 (e.g., mental underload, reduced situation awareness). In other words, when the automated driving system issues

a take-over request at the event onset (as in previous driving-simulator studies), the delayed response (and potential crash) may be the result of drivers' diminished awareness or mental underloading, but it is also affected by the time needed for drivers to become ready to act after automation.

Paper III investigated the preparation-action-time consequence further by explicitly controlling the time given to participants for their response preparation phase. The participants received either 15 s or 6 s for their response preparation (i.e., a take-over request timing of 9 or 18 s give the participants 6 or 15 s, respectively, to prepare to act before the lead-vehicle cut-out starts at about 3 s) before the lead vehicle performed the cut-out maneuver. In this way, a comparison of automation aftereffects in the lead-vehicle cut-out scenario could be conducted with the assumption of a minor influence due to the preparation-action-time-consequence. The fact that all participants performed similarly in automated driving and in the ACC baseline suggests that controlling for the preparation-action-time can reduce aftereffects and, further, that possible psychological constructs (e.g., reduced situation awareness) do not have any additional severe impact. However, driving-simulator studies typically gave drivers a shorter time budget (7 s or less) than that of Papers II and III, which included time budgets between 9 and 18 s. This means that we cannot fully disentangle the influence of the overall time budget from the influence of the relation between the timings of the take-over request and the event onset on automation aftereffects. Because humans respond to stimuli with some time delay (Macadam, 2003), there will always exist time budgets that are too short. At the other end of the spectrum, a too-long time budget may mean that the full potential of automated driving is not utilized.

Overall, the two papers provide evidence that drivers are able to resume manual control and handle safety-relevant events on real roads with a real vehicle when take-over requests are issued at 9–18 s time-to-collision and when take-over requests are issued prior to event onset. Thus, until automated driving systems are capable of providing drivers sufficient time budgets, the most advanced vehicle automation type should be assisted driving, with the driver fully responsible for the driving task at all times, despite being assisted with longitudinal and lateral control.

5.2.1.2 The influence of automation duration and timings of the take-over request on the driver response process

Finally, the results in Paper II suggest that automation duration has only a minor influence on the driver response process. This finding contrasts with those of Bourrelly et al. (2019) and Jarosch & Bengler (2019), who found that a longer automated drive resulted in more severe aftereffects, but are in line with the findings of Feldhütter et al. (2017). In fact, the only observed negative effect of automation duration on the driver response process in this paper was that four of the drivers, after being exposed to automation for 14 minutes, had problems deactivating automation on the first attempt and needed a second attempt, while all drivers successfully deactivated automation on the first attempt after only 4.5 minutes of automation. The longer duration may mean that drivers are more likely to forget the deactivation procedure.

The results in Paper III suggest that the timing of the take-over request has only a minor influence on the time needed for the actions within the response preparation phase when the take-over request is issued before event onset. This finding contrasts with previous

driving-simulator studies which indicate an increase in take-over time with an increase in the time budget (McDonald et al., 2019; Zhang et al., 2019). The likely reason behind these contrasting findings are the differences in automated driving system specifications, as was described in Section 5.2.1.1. As in most driving-simulator studies, a take-over request is issued when a situation (e.g., looming) requires an immediate response, the driver may respond to the situation rather than to the take-over request. A longer take-over request time budget in these settings likely resulted in a longer take-over time because drivers waited for the situation to become critical before starting the avoidance maneuver; there were no specific actions needed to deactivate the automated driving system before they could act on the threat (they could simply brake or steer). However, recall that in Paper III the drivers had to deactivate the automated driving system by pressing steering wheel buttons before they could respond to the event. The deactivation strategy in Paper III, selected to avoid accidental deactivation and mode confusion, required more deliberate actions and was more time-consuming than strategies in previous studies. In sum, previous findings of an increase in take-over time for an increased take-over time budget may not generalize to all types of automated driving systems. Specifically, when automated driving systems issue a take-over request before a situation requiring an immediate response, drivers may respond to the take-over request before responding to the threat itself; they may actually require a similar amount of time to deactivate the system, independent of the overall take-over time budget.

5.3 Driver response process after a period of automated driving on public road

While test-track studies have the advantage of including controlled safety-relevant events, their findings may not fully generalize to naturalistic driving studies with real traffic, which provide insights into driver behaviors in the actual environment where the systems will be used. As automated driving systems are not yet implemented in production vehicles (which might be used by novice drivers), a complete naturalistic driving study is not yet feasible. Therefore, to extend previous findings from test tracks and driving simulators, Papers IV and V investigated the safety of the driver response process when drivers receive take-over requests in real traffic in a public-road experiment.

5.3.1.1 Drivers response to take-over requests on public road

The results in Paper V suggest that drivers are able to respond to take-over requests and resume manual driving in real traffic within 10 s (i.e., before the start of a minimum-risk manoeuvre in UNECE (2021). These findings were true for all drivers, whether they chose to engage in non-driving related activities during the automated drive or not. However, a driver who is looking at an non-driving related activity item will likely take longer to perform all actions in the response process (i.e., glancing towards the instrument cluster, placing the hands on the steering wheel, deactivating the automated driving system, and placing the foot on the accelerator pedal) than a driver who is looking at the road. We can confirm a previous finding that the presence of non-driving related activities (especially handheld items) prolongs the process of resuming manual control in driving simulator studies (McDonald et al., 2019; Zhang et al., 2019).

Paper V used data collected in real traffic to assess the safety of the driver response process mainly by focusing on the response preparation phase and specifically the actions drivers performed before automation deactivation. Overall, our findings are in line with the

previous study by Naujoks et al. (2019) which found that drivers managed to safely resume manual control on German freeways. In another recent study, by Rydström et al. (2022), drivers were also able to safely resume manual control in congested traffic situations in San Francisco. In contrast to our study and the study by Naujoks et al. (2019), the researchers issued take-over requests to drivers who had no previous experience or training. This difference likely explains the significantly longer take-over times they observed.

One of the novelties in Paper V was the inclusion of drivers' foot movements, which were not considered in previous studies on automated driving in real traffic (Naujoks et al., 2019; Rydström et al., 2022). Paper V indicated that under non-critical conditions, drivers do not necessarily move their foot back to the brake pedal in response to a take-over request: only in 7% of take-over request events had participants put their foot on the brake pedal within 10 s of the take-over request. On the other hand, all participants had moved their foot back to the accelerator pedal by that time. While the response times for moving the foot back to the pedals give some indications about the manual intervention and stabilization phase, Paper V did not consider the manual driving performance in detail (unlike Papers II and III). The previous studies, conducted in real traffic, suggest (through continuous measures of lane position and steering wheel position) that drivers quickly return to a level of driving performance in line with manual baseline driving (Naujoks et al., 2019; Rydström et al., 2022).

5.3.1.2 Driver visual attention before and after take-over requests on public road

Based on the findings in Paper V and the previously cited studies conducted in real traffic, drivers (with practice) will be able to resume manual driving from an automated driving system within 10 s of a take-over request. Although none of these previous studies considered drivers' visual attention around the time of the take-over request in detail, the results in Paper IV demonstrate its importance when assessing the safety of the driver response process. The paper shows that it takes at least 15 s (longer than the 10 s needed to deactivate automation) for drivers' visual attention to reach the same levels observed during routine manual driving on the same road. For comparison, the average reported mean take-over time, based on 129 studies, is only 2.7 s (Zhang et al., 2019). As a consequence, take-over request designs based solely on the mean take-over time risk overestimating drivers' ability to perform safe manual driving after a period of automated driving. Importantly, several drivers in Paper V deactivated the automated driving system without even having looked toward the forward roadway. This sequence of actions is a safety concern, since a driver who has deactivated the automated driving system is responsible for safe manual driving and is assumed capable of handling potential events (SAE International, 2021; Thatcham Research, 2019; UNECE, 2021). In contrast to the automation aftereffects in terms of a delayed response and a degraded driving performance in a safety-relevant event, the observed automation effect in terms of a reduced visual attention after responding to a take-over request is in line with at least one previous driving-simulator study (Merat et al. 2014).

Overall, Paper IV provides significant novel findings through its detailed investigations of the visual attention levels both before and after take-over requests in real traffic, demonstrating how analyzes of drivers' visual attention (PRC over time) can identify safety-relevant driver behaviors. Furthermore, the findings in Papers IV and V suggest that drivers of future automated vehicles are likely to deactivate the automated driving

system before the start of a minimum-risk maneuver. However, deactivating automation through a button press does not necessarily mean that drivers are as aware of the environment as in manual driving (before 15 s from the take-over request have passed). It is also important to point out that both Papers IV and V are based on the assumption that the vehicle is able to handle the driving task until explicitly deactivated by the driver, and this assumption imposes several requirements on the automated driving system's capabilities. First, automated driving systems need to know about an upcoming transition demand at least 10 s (and likely longer) before the driver needs to react to changes in the traffic situation. Second, automated driving systems also need to be able to ensure that a minimum-risk manoeuvre can be performed if the driver does not respond to the transition demand.

5.4 Contributions to safe vehicle automation

The overall aim of this PhD project is to contribute to the development of objectively measurable, safe vehicle automation. This thesis demonstrates that both safe assisted driving and safe automated driving on a test track can be achieved with most drivers, because most of the drivers in Paper I and all the drivers in Paper II-III performed well in the safety-relevant events. However, since 28% of drivers in Paper I still crashed, more work is needed to understand how to prevent drivers from crashing in safety-relevant events encountered in assisted driving (with no vehicle notification). Papers II and III demonstrate that the take-over request issued in automated driving may help drivers respond appropriately during safety-relevant events after automation has been deactivated. In fact, these papers demonstrate that drivers coming out of automated driving are able to perform manual driving and respond to safety-relevant events encountered after the take-over request in a manner similar to drivers driving manually or driving with ACC.

Furthermore, this thesis demonstrates that knowledge about safe vehicle automation can be obtained by investigations of the driver response process during assisted driving and after automated driving, and the factors that influence this process. A challenge for the future is to integrate this knowledge into the design process. As a step in that direction, this thesis can inform the development of, for example, vehicle automation design, vehicle regulations and consumer rating protocols, driver monitoring systems and driver models.

To begin with, this thesis demonstrates the need to consider detailed analyzes of drivers' visual attention (along with take-over times) in order to understand the safety implications of automated driving systems—and consequently, to make informed decisions about vehicle automation design. As noted, focusing only on the time it takes for drivers to deactivate an automated driving system risks overestimating drivers' readiness to respond to potential threats (because drivers may not yet be looking at the road). One way to assess drivers' visual attention levels before and after take-over requests is through driver monitoring systems. These systems are likely to become reality in future vehicles, as Euro NCAP's consumer rating program plans to give high scores to vehicles equipped with driver monitoring systems starting in 2023 (Euro NCAP, 2022). One example of the benefit of a driver monitoring system is that the system could anticipate or postpone take-over requests based on the driver's visual attention levels during automated driving.

Second, the findings in this thesis can be used to inform vehicle regulations for current and future assisted driving and automated driving systems. The findings in Paper I show that requiring drivers to keep their hands on the wheel during assisted driving will not necessarily prompt earlier responses in longitudinal scenarios caused by system limitations, although (as mentioned) the requirement may have other safety benefits. The findings in Papers II, III, and V suggest that, most drivers using an automated driving systems are able to deactivate the system and resume manual control within 10 s—as currently assumed in UNECE (2021). However, there is not one single response time that is unique to every driver or situation. In fact, the combined findings in Papers II, III, and V suggest that participants, on average, need 0.7 s to direct their first glance at the instrument cluster, 1.2–2.2 s to place their hands on the steering wheel, and 2.9–4.1 s to deactivate automation. However, some participants needed up to 6–7 s to direct their first glance at the instrument cluster, 8.7 s to place their hands on the steering wheel, and 11.6 s to deactivate automation.

Third, the newly acquired knowledge about the response process can be used to develop quantitative driver models that can be: (a) included in computational simulations for assessing the safety impact of design choices for human-machine interfaces or take-over request designs or (b) used together with driver monitoring systems to develop countermeasures for unsafe behaviors: behaviors detected by a driver monitoring system can be compared to a safe reference behavior and a countermeasure could act on potential deviations. Since the driver response process differs for assisted driving with no vehicle notification and automated driving with a take-over request, it makes sense to develop separate models for these fundamentally different automation types and driver roles. In addition, driver models for assisted driving need to capture the behavior of drivers that crash due to an expectation mismatch, possibly using the PP framework that includes different generative models.

Finally, this thesis can also impact automated driving system design principles (e.g., human-machine interfaces for transitions). Whereas a period of 9.5 minutes (i.e., difference between 14 and 4.5 minute durations) of automated driving does not seem to have any effect on the driver's ability to perform manual driving after a transition, an improved human-machine interface design can make the transition more intuitive so that drivers will be less likely to forget how to deactivate the system, even after a long period of automation. When an automated driving system is capable of issuing take-over requests prior to event onset, an earlier take-over request does not seem to prolong the drivers' response preparation process. In fact, when the deactivation strategy requires a deliberate button press, drivers seem to respond to a take-over request issued before event onset independently of situation kinematics. Therefore, earlier take-over requests can give drivers more time to assess the traffic environment and notice upcoming events, which may lead to precautionary braking. Overall, allowing engagement in non-driving related activities in automated driving will typically prolong the time required for driver response preparation, but drivers should still be able to deactivate automation within 10 s of the take-over request.

5.5 Limitations

Although the experiments in Papers I–III are performed with a real vehicle on a test track, which provides a higher degree of realism than a driving simulator, a test-track study also has its limitations. The situation is not perfectly realistic; it lacks real traffic, and a test

leader and safety driver are in the vehicle. In addition, the conflict objects used in the three experiments lacked some realism for safety reasons. In the experiments for Papers I and III, the conflict object was a balloon car or a stuffed garbage bag, and in the experiment for Paper II the conflict object was a simulated road-work zone made of cones. However, it would not be safe to perform studies which include a safety-relevant event on a public road with real traffic—only non-critical scenarios could be investigated. The public road experiment (Papers IV and V) also has limiting factors that may hinder generalization. For example, the experiments were conducted on Swedish highways in daylight and may not generalize to other cultures and weather conditions. In addition, this thesis primarily inferred drivers' visual attention levels from the direction of their gaze. Since gazing towards an area does not guarantee that it is being attended to, this inference is a potential limiting factor of our study. As an additional limitation, the drivers in the experiments in Papers I–V were Volvo car employees in the Gothenburg area in Sweden. The extent to which our results generalize to other populations remains unknown.

6 Conclusions and future work

This thesis has advanced the knowledge of human factors in vehicle automation through detailed analyzes of the driver response process, using data collected with a real vehicle on real roads. The findings contribute to our understanding of automation effects and aftereffects, as well as the contributing factors influencing the size of these effects.

To begin with, this thesis demonstrates that vehicle automation does not always result in detrimental automation effects in terms of unsafe driver response and performance whether in safety-relevant events on a test track with real vehicles or when responding to take-over requests in real traffic. In fact, most drivers 72% of the drivers in Paper I (Objective I) and 100% of the drivers in Papers II and III (Objectives II and III), were able to perform safe manual driving and intervention performance after a period of assisted driving and automated driving. This thesis has revealed less severe automation effects than those that had been observed in virtual settings (driving simulators). When take-over requests are issued well ahead of the need for drivers to resume manual control (e.g., 10 s before the start of a minimum risk maneuver as recently proposed by current vehicle regulations), drivers are able resume manual driving in time (Objectives II, III, and IV). To guide countermeasure designs, vehicle regulations, and driver monitoring systems, we need to understand if the automation aftereffects observed in previous studies but not in our studies, are simply a result of 1) the test environments (driving simulators vs. test track/public roads) and 2) the time needed for drivers to become ready to act (i.e., to complete the actions within the response preparation phase. As a first step, a driving simulator study and a test track study could be performed with the exact same setup in order to understand if the larger automation aftereffects observed in driving simulators are due to the test environment, or if the effects are more related to the timings of take-over request and event onset. Overall it is important to disentangle automation effects that merely stem from the time needed to prepare for action (i.e., automation effects due to the preparation-action-time consequence) before attributing potential effects to a psychological construct or cognitive mechanism (e.g., a reduced situation awareness).

In addition, this thesis also demonstrates that what is safe for automated driving is not necessarily safe for assisted driving and vice versa (Objectives I and III). Thus, future work should state what type of automation (including assumptions on driver responsibilities), is being investigated. As noted in Paper I, after having supervised a near-perfect assisted driving system for thirty minutes, some drivers may crash, despite having eyes on the threat and hands on the steering wheel, since they do not understand the need to act in a safety-relevant event that is not preceded by a vehicle notification. Although keeping their hands on the wheel might neither help drivers avoid crashing nor elicit earlier steering responses in longitudinal conflicts, the position may help drivers become aware of incorrect/insufficient system steering or prevent misuse (e.g., non-driving related task engagement when not allowed by system design). As long as automation limitations contribute to crashes, we need to find ways to prevent these crashes. For example, a design that requires drivers to put their hands on the steering wheel and apply torque occasionally may ensure that the driver is sufficiently engaged in the driving task to respond to events when needed. Also, , when the same safety-relevant event is preceded by a take-over request (in automated driving), drivers appear to better understand their responsibility to handle events and avoid crashing.

Overall, this thesis demonstrates the effects of the test environment, automation design and time budgets on automation effects (Objectives II and III). Therefore, to make vehicle automation as safe as possible, future researchers should aim to perform experiments that replicate automated driving systems and scenarios, likely to be present in real traffic. Future automated driving systems (which are in line with future vehicle regulations and insurance company definitions) on public roads are unlikely to expect drivers to respond to urgent non-prompted events. Before we have automated driving systems that can issue a take-over request to signal the need for manual driving, assisted driving in combination with system-limitation events requires further research to ensure that drivers understand their responsibility to act when such limitations occur.

Also, an important challenge for future automated driving systems is the potential for deskilling (reduced manual driving performance skills when one rarely drives manually) as the systems become more capable. Although this thesis demonstrates that automated driving has no severe short-term effects on manual driving performance, it is unclear whether—and if so, when—drivers start to lose their manual driving skills. In addition, the findings in this thesis are based on drivers who are awake and in a traditional seating position. Future research should investigate what other options during automated driving which still leave the driver available to respond to take-over requests (e.g., sleeping, adopting different seating postures).

Finally, this thesis demonstrates the importance of including detailed investigations of the driver visual attention as part of the driver response process; it is not only the timing and quality of driver actions in response to take-over requests and/or safety-relevant events and the manual driving performance after automation that matters for assessing the safety of vehicle automation. Considering the drivers' visual attention levels (inferred from gaze direction and glance durations in this thesis) during and after the transition to manual driving is important, since some drivers may deactivate automation before looking on-road (Objective IV). In addition, after being exposed to automation, drivers may need longer than 15 s to establish the same visual attention levels observed during manual routine driving. Thus, if vehicle automation is designed solely based on the time needed to deactivate automation, the safety may be overestimated as drivers' may deactivate automation before being as attentive as in manual driving.

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