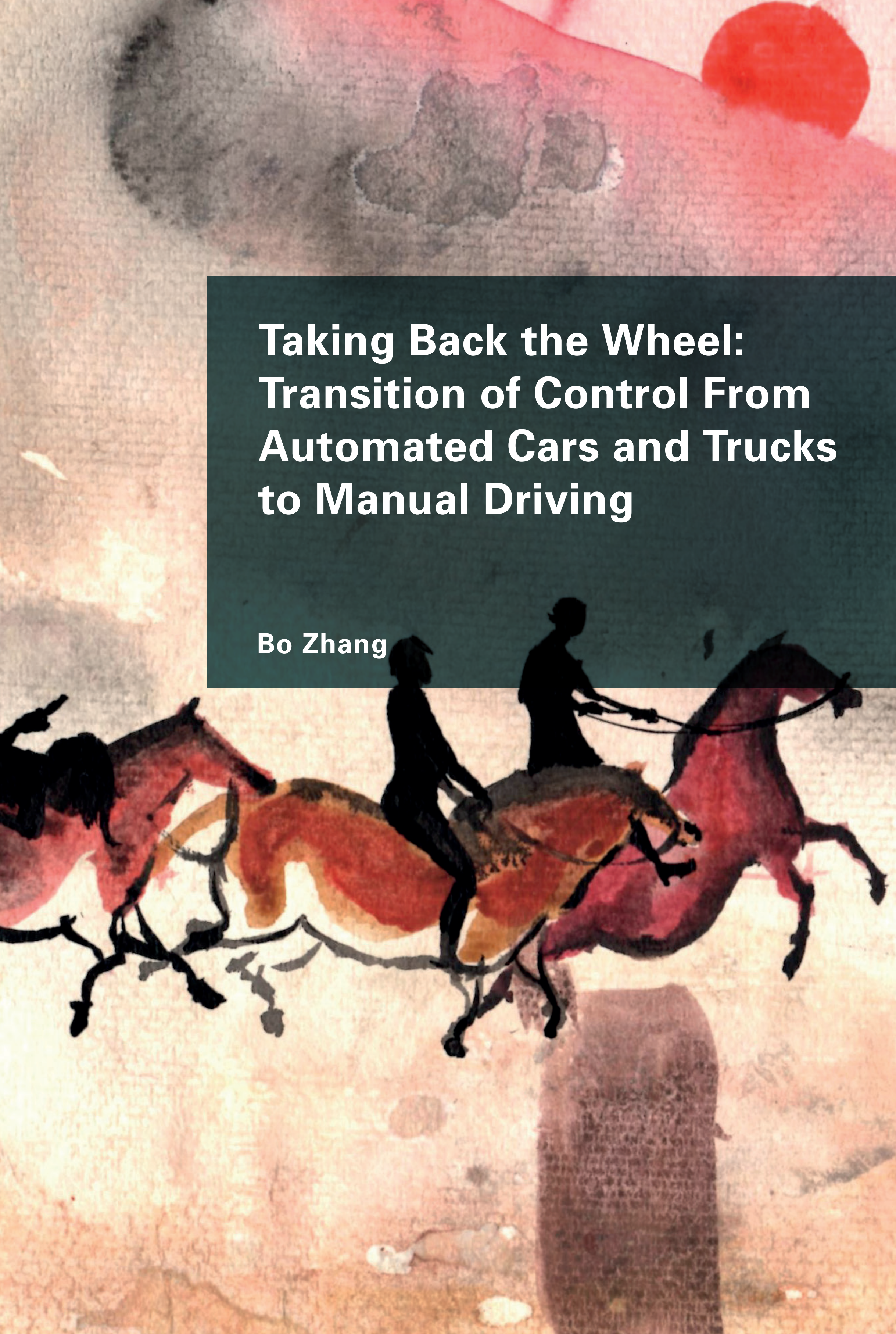
Taking Back the Wheel: Transition of Control From Automated Cars and Trucks to Manual Driving

Bo Zhang



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University of Twente

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Cover illustration by Bo Zhang, inspired by the H-Metaphor that driving automated vehicles is like riding horses (Flemisch et al., 2003).

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DISSERTATION

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in Heilongjiang, China

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Dedicated to

My Mother Yuehua Zhang, who named her daughter 'Bo (博)' hoping that she would become a PhD (博士) one day. Your dream now has come true.

献给我的妈妈张月华：

亲爱的妈妈，您的女儿张博终于成为张博士了，您的梦想实现了！

Preface

This thesis is the result of a PhD research carried out at University of Twente, Department Centre for Transport Studies from 2016 to 2020. Now this long journey has finally come to an end, filled with treasurable experiences that have shaped me into a qualified scientific researcher, a persevering person, and a critical thinker. Through all the ups and downs I was never alone, and I would like to express my sincere gratitude to all people who made this possible.

First of all, I would like to thank my promotors Marieke Martens and Eric van Berkum. They believed in my potentials and provided me the great opportunity to join their Department and develop my personal and professional skills. I am particularly grateful to Marieke for her all-round guidance and support. Thank you, Marieke, for sharing your invaluable experience and perspective as a successful female scientist, for helping me through the obstacles when the road got bumpy, and for all the inspiring and encouraging talks that lit up my day and kept me going steadily towards completing my PhD. My special thanks also go to Riender Happee and Joost de Winter at TU Delft, who welcomed me into the HFauto family, hosted my secondment in the early stage of my PhD, and provided continuous supervision and mentoring throughout my studies. Thank you Riender for reaching out to me and introducing me to Marieke when I was a fresh master graduate; my journey started because of you. Joost, your high standard of academic research pushed me further than I could imagine, and I will forever benefit from what I have learned from you. I am very grateful to Klaus Bengler for hosting my secondment at my old school TU Munich. Thank you for introducing me to the fantastic realm of Human Factors, and for supporting every important decision in my study and career.

An essential part of my research concerns driver behaviour in automated platooning scenarios, and this could not be completed without generous support from the amazing colleagues at TNO. I am grateful to have participated in the TNO Early Research Program (ERP) Human Enhancement: Adaptive Automation, and to have the access to large amounts of experimental data that formed the base for four chapters in this thesis. I want to express my deep gratitude to Ellen Wilschut, Dehlia Willemsen, and Jeroen Hogema for their invaluable scientific advice and contributions as co-authors, to Ingmar Stel for technical support, and to Bart Joosten for inspiring brainstorm sessions. My thanks also go to Tom Alkim at Rijkswaterstraat for giving me the opportunity to work on the see-through truck study and for revising the manuscript for publication.

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I would like to thank all my HFauto research fellows for sharing their knowledge and expertise in diverse research areas, and for the fantastic time at the consortium meetings. Many thanks to Silvia Varotto and Zhenji Lu at TU Delft for their invaluable contributions to two important chapters of my thesis, and for their encouragement and companion as friends. Thanks to Marjan Hagenzieker, Christopher Cabrall, Pavlo Bazilinskyy, and Miltos Kyriakidis at TU Delft, Daniel Heikoop, Alexander Eriksson and Neville Stanton at the University of Southampton, Joel Gonçalves, Bastiaan Petermeijer and Klaus Bengler at the TU Munich, Matt Sassman, Thierry Bellet and Marie-Pierre Bruyas at IFSTTAR Lyon, Alberto Morando and Marco Dozza at Chalmers University of Technology, Ignacio Solis, Veronika Petrovych, Katja Kircher, Jan Andersson, and Magnus Hjälmdahl at VTI Linköping. I feel lucky to be part of the big family and to learn from you at the early stage of my training, which helped kick-start my research. I'm also grateful to fellow researchers outside the HFauto consortium, Anna Feldhütter and Andre Dietrich at TU Munich, for supporting the experiment during my joint secondment with Zhenji.

Many thanks also go to my colleagues at the Department Centre for Transport Studies, University of Twente: Amelia Huang, IG Ayu Andani, Anika Boelhouwer, Francesco Walker, Tom Thomas, Kasper van Zuilekom, Mariska van Essen, Oskar Eikenbroek, Karst Geurs, Lissy La Paix Puello, John Pritchard, Tiago Fioreze, and others. Thank you for all the good time we spent together and for the inspiring discussions during lunch and coffee breaks. Many thanks to our secretary Dorette Olthof for making me feel at home from day one.

My life would be pale and I would never come this far without wonderful friendship developed along the way. Special thanks go to my paranymphs Ellen Wilschut and Silvia Varotto. Ellen, thank you for your strong support in every possible aspect in my career and personal life, and for your dedicated Dutch translation of the *Samenvattig* of my thesis. Silvia, thank you for your company and support throughout my journey. We share happiness and sorrow, and grow stronger together. My sincere gratitude also goes to my teachers and classmates at the Gerrit Rietveld Academy. It takes great courage to develop my Alter Ego as a visual artist besides being a scientific researcher; thank you all for keeping me going this far and staying true to myself. Thanks to all those who dropped a random "how's going" that distracted me from a blue, unproductive day.

I cannot express how grateful I am to my beloved family. Thank you, Fanyu, my husband and best friend in life, for your love, encouragement, patience, tolerance, and understandings, for your constructive and practical suggestions as a mature PhD researcher, and for respecting and supporting my bold decisions and wildest dreams. Thank you, my mom Yuehua Zhang, for your unconditional love and for being my role model as a decent, modest, strong, and independent woman. I'm always proud of being your daughter and I hope at this moment you feel proud too. To Amélie, Heidi, Penny, Pavarotti, Yellow, Grey, and Pipi, the cutest little living creatures keeping my company through the lonely days.

I'm so lucky and proud to have you all along my journey.

Bo Zhang
Amersfoort, The Netherlands, January 2021

Content

List of Abbreviations and Acronyms

ACC	Adaptive Cruise Control
ADAS	Advanced Driver Assistance System
AD	Automated Driving
ADS	Automated Driving System
AOI	Area of Interest
BE	Brake Event
BRT	Brake Response Time
CACC	Cooperative Adaptive Cruise Control
CAV	Connected and Automated Vehicle
DDT	Dynamic Driving task
DOF	Degree of Freedom
HMI	Human-Machine Interface
ICC	Interclass Correlation Coefficient
ITS	Intelligent Transportation Systems
LKAS	Lane Keeping Assist System
MD	Manual Driving
MR	Monitoring Request

MRT	Movement Response Time
NDT	Non-Driving Task
ODD	Operational Design Domain
OEDR	Object and Event Detection and Response
PRT	Perception Response Time
RT	Response Time
SAE	Society of Automotive Engineers
SD	Standard Deviation
SDLP	Standard Deviation Lane Position
SPD	Speed
STS	See-Through System
SWA	Steering Wheel Angle
THW	Time Headway
TO	Take-over
TOT	Take-over Time
TRT	Total Response Time
TTC	Time to Collision

1. Introduction

1.1 General introduction and problem statement

Motor vehicles radically changed the way we live and work, ever since its introduction 130 years ago. Although they have often been a symbol of independence and freedom (Steg, 2005), times are changing and the negative impacts are getting more and more attention, such as road accidents, traffic congestion, and pollutant emissions. According to the World Health Organization (2018), every year more than 1.3 million people worldwide are killed, and up to 50 million are injured in road traffic crashes. The National Highway Traffic Safety Administration (NHTSA) estimates that "dangerous choices or errors people made behind the wheel" contribute to more than 90% of serious crashes, which can be caused by various human-related factors such as intentional violations, attention lapses, distraction, fatigue, and alcohol use. Automated driving technology has great potential to fundamentally solve road traffic issues and improve our quality of life (Fragnant & Kockelman, 2015; Kyriakidis et al., 2019). By assisting or replacing human operation in normal and critical driving tasks, serious crashes that are dominantly caused by human errors are assumed to be largely reduced. If connected and coordinated through advanced communication systems in the form of a platoon, automated vehicles are able to travel safely even with much smaller headways, which can largely increase road capacity, improve traffic flow efficiency, and reduce energy consumption (Coppola & Silvestri, 2019; Rios-Torres & Malikopoulos; 2017, Shladover, 2018; Talebpour & Mahmassani, 2016).

Decades of effort and technology advancement seem to bring automated vehicles from science fiction fantasy closer to reality, but a long and windy road is still ahead to the realization of full automation where no human intervention would be needed in any road situation. Safe human-system interactions, particularly at transitions of control to the driver when the system cannot cope with the current driving situation, pose key challenges for a successful deployment of automated intelligent systems at different stages of development. When the system is less capable and reliable, the driver has to closely monitor the system and take over imminent manual control when necessary. This challenges humans' inherent weak point of staying vigilant over a prolonged period of time (Mackworth, 1948; Davies & Parasuraman, 1982;

Parasuraman 1987), and drivers' capability to respond adequately within a short time budget (Banks, Eriksson, O'Donoghue, & Stanton, 2018; Casner, Hutchins, & Norman, 2016). When the technology becomes more mature, the system is supposed to largely replace human operation in most situations. However, even in these cases, driver interventions due to system limitations or failures, or the exceedance of the system's operational limits are still needed. A main challenge at this stage is how drivers respond in these conditions and how they can be supported in taking back control in a safe and smooth manner.

Since the past decade, an increasing number of studies have addressed human factors issues related to control transitions (for an overview, see Lu, Happee, Cabrall, Kyriakidis, & De Winter, 2016 and Kyriakidis et al., 2019), and suggest that multiple factors related to the driver, the automation system, and the situation potentially influence driver readiness to take back control. This means that no single criterion for an optimal take-over time budget exists today that fits all drivers in all situations, and design solutions are called for to support individual drivers in taking over control. To achieve this goal, a good understanding of driver take-over process and the variability between and within drivers is needed, which requires further efforts because the large majority of studies merely focus on mean take-over response times measured in stand-alone automated car scenarios. This thesis tackles the issues stated above and investigates driver behaviour and performance at control transitions and the variability, particularly in automated platooning scenarios. The aim is to contribute to designing safe and comfortable control transitions to manual.

The following part of this chapter first provides a state of the art on development of automated driving (Section 1.2), then introduces levels of driving automation and related human factors challenges (Section 1.3), followed by fundamental knowledge on transitions of control, driver take-over process, and driver take-over performance (Section 1.4). In Section 1.5, the research objectives and research questions are formulated and explained. The overall structure of the thesis is outlined in Section 1.6.

1.2 Development of automated driving

Even long before the wish to solve traffic safety issues by means of automated vehicles, people started to dream of cars driving by themselves. One very early prototype of "driverless" cars dates back to mid-1920s when Houdina Radio Control demonstrated "American Wonder" in New York – a 1926 Chandler controlled by the following car via radio impulses (Time Magazine, 1925). At the 1939 World's Fair in New York, General Motors sponsored the "Futurama" exhibit to envision American lifestyle 20 years in the future. The highlight was an infrastructure system that could guide radio-controlled cars through electromagnetic fields embedded within the roadways, which was generally seen as the first proposal of an automated highway system in the world. In the late 1950s, General Motor together with the Radio Corporation of America (RCA) brought this idea to life and demonstrated a full-size electric guide-wire system on a test track that enabled automated lateral and longitudinal control of vehicles. Research and development that revolved around this concept continued for another 20-30 years in the United States, UK, Germany, and Japan.

From the 1980s, the rapid advances in electronics, computers, communications, controls, and sensor technologies started to shape modern automated driving systems that operate mainly based on onboard sensors and control units without dedicated infrastructure support (also known as stand-alone automation systems). In the early 1980s, Ernst Dickmanns and his team at Bundeswehr University Munich developed the first automated vehicle of this type: a Mercedes van incorporating a vision-based system that was capable of detecting road markings and controlling steering wheel, throttle, and brakes of the van based on real-time evaluation of image sequence. In successive years, various projects tackling technological challenges in automated driving and practical road traffic problems were launched worldwide, including the EUREKA Prometheus project of the European Union (Williams and Preston, 1987), the DARPA Autonomous Land Vehicle (ALV) project in the United States (Schefter, 1985), and the Super-Smart Vehicle Systems program in Japan (Tsugawa, 1991). These intensive research and development efforts largely increased the capability and efficiency of vehicle automation, as evidenced by a series of successful demonstrations and challenges conducted during the 1990s and 2000s, such as DARPA Grand Challenges (Buehler, Iagnemma, & Singh, 2007) and the Urban Challenge (Buehler, Iagnemma, & Singh, 2009).

In the late 2000s and the early 2010s, Google and many major automotive manufacturers initiated commercial research on automated driving systems and began various testing on public roads. Meanwhile, several core advanced driver assistance systems (ADAS) such as adaptive cruise control (ACC) and lane keeping assist systems (LKAS) were gradually introduced to the market. Driving automation began to receive considerable attention in mass media, raising increasing interest in publicity and industry. In 2015, Tesla became one of the first car manufacturers to release partial automated driving features (Autopilot) to its customers, followed by other major automakers including BMW, Mercedes Benz, Audi, and VOLVO. Incorporating multiple advanced sensors (e.g., stereo camera, radar, and ultrasonic sensor) and enhanced processing capabilities, these commercialized automation systems are able to conduct longitudinal and lateral control of the vehicle in simple traffic situations under non-adverse weather conditions. Despite the image that is being presented by some users, industry or the media, the driver of these commercially available vehicles has to constantly monitor the driving environment and be prepared to take immediate control when necessary since its functioning is not reliable yet. Around 2015, at the time of the introduction of Autopilot by Tesla, the concept of automated driving reached its peak in expectation in the Hype Cycle (Figure 1.1 Left), implying an expected mainstream adoption within 5 to 10 years

As more time passed, the high expectations have diminished to a more realistic level in 2019 (Figure 1.1 Right), due to increasing real-world experience with automated driving technology and a better understanding of its capabilities and limitations (for an overview of expert opinions, see Bazilinskyy, Kyriakidis, Dodou, & De Winter, 2019). For example, it is now more widely recognized that currently, commercially available automation systems requiring constant driver supervision involve safety risks (for an overview of expert opinions, see Kyriakidis et al., 2019), as evidenced by a number of fatalities involving Autopilot that occurred in recent years (Mider, 2019). Also in the Netherlands, the Dutch Safety Board has identified a number of new road safety risks associated with current commercially available vehicles with automated functions (Dutch Safety Board, 2019).

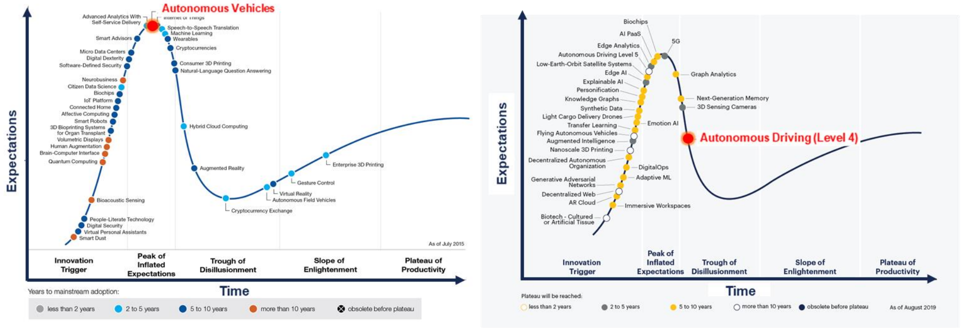

Figure 1.1: Gartner Hype Cycle for Emerging Technologies illustrated for the year 2015 (Left) and 2019 (Right). The red circles highlight the position of automated driving technology.

In parallel with the development of stand-alone automated vehicles, extensive research on connected automated vehicles began in the late 1980s with the California PATH (Partners for Advanced Transportation Technology) program. The core concept is to operate vehicles in platoons, in which virtually connected vehicles travel closely together as one cooperative system, with its primary goal to maximize highway capacity, energy efficiency, and safety (Shladover, 2006). The early research of PATH focused on passenger cars platoons, revolving around the idea that all vehicles (including the platoon leader) would be fully automated on dedicated lanes to eliminate negative impact caused by human error. Since the late 1990s, research and development interest has shifted towards platooning of heavy-duty trucks, largely driven by the fuel economy in freight transportation (Tsugawa, 2013). Advanced longitudinal control functionalities that combine onboard sensors and vehicle-to-vehicle (V2V) communication, such as cooperative adaptive cruise control (CACC), have also become subjects of intensive research to achieve more flexible and reliable platooning systems. Although platooning has not yet been deployed in commercial use, current efforts are made towards operating truck platooning in real life cases and implementation of multi-brand platooning (e.g., ENSEMBLE, see Willemsen et al., 2018). A milestone is the European Truck Platooning Challenge initiated by the Dutch EU Presidency, in which six European truck manufactures brought truck platoons onto public roads for the first time, travelling from various European cities to the final destination of the port of Rotterdam in the Netherlands in April 2016. Due to safety concern and legal issues, the trucks participating in the challenge only performed automated longitudinal control, despite the capability of automated steering as demonstrated on test tracks, leaving an important role for the human in the platooning scenarios.

1.3 Levels of driving automation and human factors issues

It can be seen that automated vehicles of various forms are merging into our roadways more or less along an evolutionary path. As the capability of a driving automation system increases, a wider range of driving tasks could be carried out by the system, leading to a reduction in human engagement and a change in the role of the human driver. It is highly important to provide common classifications that facilitate the exchange of knowledge across domains, and to avoid confusion and imprecisions when describing system functionalities and limitations (Shladover, 2018).

Michon’s (1985) hierarchical structure is typically referenced to categorize manual driving tasks, which comprises three levels. The lowest level (operational level) concerns longitudinal and lateral motion control to maintain the vehicle’s lane position in traffic, which are normally carried out with little cognitive effort. At the intermediate level (tactical level), driving manoeuvres are planned and executed based on the pre-defined goals and in response to the objects and events in the driving environment, which normally requires greater mental efforts, and more elaborate physical movement. Examples of such manoeuvres are a lane change, obstacle avoidance, and overtaking. At the highest level (strategical level), the general planning of a trip is conducted, including scheduling of the trip and selection of destinations and routes. At the current stage, automated vehicles are mainly expected to carry over driving tasks at the operational and the tactical levels, which are often referred to as dynamic driving tasks (SAE, 2018; Merat et al., 2019).

The German Federal Highway Research Institute (BASt; Gasser & Westhoff, 2012), the United States National Highway Traffic Safety Administration (NHTSA, 2013), and the Society of Automotive Engineers (SAE, 2018) have each developed a taxonomy of levels of driving automation. Despite differences in definitions and terminologies, the three taxonomies share similar criteria to categorize the automated driving systems, mainly based on how primary dynamic driving tasks (i.e., longitudinal and lateral vehicle motion control, and monitoring of the driving environment) are distributed between the human driver and the automation system (Lu et al., 2016). Because the SAE taxonomy provides relatively more precise definitions and is the most-cited reference for automated-vehicle capabilities in both industry and academic research (Shuttleworth, 2019), it is adopted in this thesis and is explained below (according to the latest version released in 2018).

As depicted in Table 1.1, six levels of driving automation are defined by SAE (2018), ranging from SAE L0 (no driving automation) to SAE L5 (full driving automation). Differences between levels are primarily determined by means of who is performing the dynamic driving task, who is the fallback-ready agent (i.e., who performs the dynamic driving tasks in case of system failures), the limit of the operational design domain (ODD, the specific conditions under which the system is supposed to function), and the role that is required of the driver in that specific level.

SAE L0 is equivalent to manual driving, which means that the driver executes all dynamic driving tasks, possibly assisted by lower levels of ADAS that provide warnings or momentary assistance (e.g., emergency braking assistance).

In SAE L1 (Driver assistance), the driving automation system executes either longitudinal or lateral control of the vehicle, while the driver performs the remaining dynamic driving tasks. Examples of such systems are the Adaptive Cruise Control (ACC) or Lane-Keeping System (LKS).

In SAE L2 (Partial driving automation), vehicle motion control in both dimensions are executed by the system (e.g., combining ACC and LKS), but the driver is required to constantly monitor the driving environment and supervise the system, and intervene as necessary to maintain safe operation of the vehicle even without notification. From this level on (L3 and higher), the human driver’s role as an active operator is fundamentally changed.

In SAE L3 (Conditional driving automation) and L4 (High driving automation), the system performs all dynamic driving tasks within the limit of the ODD, so the driver does not need to permanently monitoring the driving environment and is allowed to engage in non-driving tasks. This is the level where automated driving becomes interesting for users, since they can make better use of travel time for work and relaxation. A SAE L3 system expects the driver to intervene in case the system approaches the limits of its ODD (for instance when approaching a workzone or extreme weather conditions) or when system failures occur (i.e., the driver serves as the fallback-ready user within a reasonable time budget because the camera is obstructed). The system is capable to determine the necessity for driver intervention and issues a timely request to intervene (also known as take over request (TOR) in a rich body of literature). In SAE L4, the system does not primarily rely on the driver to be the fallback-ready user, even though a request to take back control may be provided. In case a system failure occurs or the driver does not respond to the issued request, the system performs the fallback itself and transitions automatically to a minimal risk condition (e.g., conducting an emergency stop at a 'safe' spot). Currently, SAE L4 automation is predominantly developed for public transport concepts such as last mile transits and automated shuttle buses on limited trajectories. Public transport solutions will not be part of this thesis since there is no transition of control back to manual driving.

In SAE L5 (Full driving automation), the system is capable of all dynamic driving tasks in all situations (i.e., the ODD is unlimited) without involvement from human drivers. However even there, some situations may occur where the car cannot continue, such as flooded roads or extreme snow storms. Since L5 vehicles are not designed for a transition of control, this level will also not be discussed in this thesis.

There have been discussions that the taxonomies with numbered levels may induce misinterpretation and false expectation among the public, because the ascending levels do not necessarily correspond to the actual evolution of the technology (Templeton, 2014). For instance, a L3 system may be only available during traffic congestions with speeds under 50km/h in the operational design domain, whereas on a trip without any congestion, it will not have this level available at all. And even with a L4 system, it still may be the case that it may only work on motorways for 10% of the time, and not be available on other roads or under adverse weather conditions. Some also argue that the SAE levels are not sufficient to describe the variety of automation systems, for instance public transport on pre-defined routes only, or systems that are related to connected and cooperative technology (e.g., automated platooning systems). Due to the very short inter-vehicular gaps, it is very risky for drivers in a platoon to respond to longitudinal critical events in case of system failures, so the platooning system should perform the fallback even in lower SAE levels. In addition, the lead vehicle is normally operated by a professional driver in a lower level of automation (e.g., in SAE L0 or L1) than the following vehicles (e.g., in SAE L3 or L4), which makes it difficult to apply the SAE taxonomy to the whole platooning system.

Despite the limitations of the SAE levels to describe all possible types of automation, the key element remains the role of the human driver in driving tasks. Irrespective of whether a vehicle does or does not use cooperative technology or has an extended or a limited operational design domain, it is important to know if the driver needs to monitor the road or not, and what will happen when a driver needs to intervene under various conditions. While it may be true that only fully automated vehicles that completely remove driver responsibilities throughout the ride could maximize safety benefits of driving automation, experts generally believe that there is still a long way to go until this ultimate goal can be achieved (Kyriakidis et al., 2019; Shladover, 2016; Gomes, 2014; Underwood, 2014; Yoshida, 2014). As long as human intervention in any form is still expected, a safe human-automation interaction would play a central role in a successful deployment of driving automation on public roads (Carsten & Martens, 2019).

Table 1.1: Summary of levels of driving automation defined by SAE (2016). DDT = Dynamic driving task, OEDR = Object and event detection and response (incl. monitoring the driving environment and the automation system), ODD = Operational design domain, ADS = Automated driving system.

Level	Name	Narrative definition	DDT: Sustained lateral and longitudinal vehicle motion control	DDT: OEDR	DDT fallback	ODD
Driver performs part or all of the DDT						
0	**No Driving Automation**	The performance by the driver of the entire DDT, even when enhanced by active safety systems.	*Driver*	*Driver*	*Driver*	n/a
1	**Driver Assistance**	The sustained and ODD-specific execution by a driving automation system of either the lateral or the longitudinal vehicle motion control subtask of the DDT (but not both simultaneously) with the expectation that the driver performs the remainder of the DDT.	*Driver and system*	*Driver*	*Driver*	Limited
2	**Partial Driving Automation**	The sustained and ODD-specific execution by a driving automation system of both the lateral and longitudinal vehicle motion control subtasks of the DDT with the expectation that the driver completes the OEDR subtask and supervises the driving automation system.	***System***	*Driver*	*Driver*	Limited
ADS ("System") performs the entire DDT (while engaged)						
3	**Conditional Driving Automation**	The sustained and ODD-specific performance by an ADS of the entire DDT with the expectation that the DDT fallback-ready user is receptive to ADS-issued requests to intervene, as well as to DDT performance-relevant system failures in other vehicle systems, and will respond appropriately.	*System*	***System***	*Fallback-ready user (becomes the driver during fallback)*	Limited
4	**High Driving Automation**	The sustained and ODD-specific performance by an ADS of the entire DDT and DDT fallback without any expectation that a user will respond to a request to intervene.	*System*	*System*	***System***	Limited
5	**Full Driving Automation**	The sustained and unconditional (i.e., not ODD-specific) performance by an ADS of the entire DDT and DDT fallback without any expectation that a user will respond to a request to intervene.	*System*	*System*	*System*	**Unlimited**

An increasing number of studies have addressed human factors issues that hinder drivers' capabilities to maintain safe control at different levels of automation (Saffarian, De Winter, &

Happee, 2012; Van den Beukel; & Martens, 2013; Cunningham, & Regan, 2015; Kyriakidis et al., 2019; Navarro, 2019). In partial automation (SAE L2), the current state of technology requires the driver to be prepared for imminent intervention and does not allow drivers to be able to take their eyes off the road. Therefore, it is crucial to constantly keep the driver in the monitoring loop, so that a high level of situation awareness (Endsley, 1995) can be maintained. The problem with this is that humans are by nature poor at vigilance tasks (i.e., to sustain concentrated attention and respond to irregular and infrequent target stimuli for extended period), as is the case with monitoring driving automation systems (Onnasch, Wickens, Li, & Manzey, 2014; Norman, 2015). Accumulating evidence suggests that vigilance performance (e.g., detection accuracy and response speed) inevitably declines over time on task due to the depletion of attentional resources (Mackworth, 1948; Davies & Parasuraman, 1982; Parasuraman 1987; Scerbo, 2001). The monotonous nature of monitoring tasks would also induce intentional or unintentional attention switching towards task-unrelated thoughts and stimuli (Scerbo, 1998; Helton et al., 2005; Casner & Schooler, 2015), and consequently cause a loss of situation awareness.

In addition, overreliance (or complacency), resulting from inappropriately high trust (overtrust) in automation, is another major cause for monitoring failures (Ensley, 2017; Singh, Molloy& Parasuraman, 1993; Parasuraman & Riley, 1997; Carsten & Martens, 2019). Poor trust calibration is directly associated with an inaccurate mental model of system capabilities and limitations, which can be caused by insufficient information provided about system functionalities, little or no feedback on the system status, and a lack of prior experience with such systems (Lee & See, 2014; Endsley, 2017; Walker, Wang, Martens, & Verwey, 2018; Carsten & Martens, 2019). Also, for people it may seem counter-intuitive that they are driving cars with automated functions, without any of the benefits of vehicle automation such as being able to (temporarily) do something else.

In higher levels of automation (SAE L3 and L4), the driver would be allowed to be temporarily out of the monitoring loop and to engage in a wide range of non-driving tasks (Naujoks, Befelein, Wiedemann, & Neukum, 2017), which would result in a large variability in drivers' activities, mental states, and body postures. How the systems can adapt to broad variations within and between drivers in taking over control, becomes the main challenge at this stage. Great caution is also needed to minimize automation surprises caused by unexpected system performance (Sarter & Woods, 1997), which are more prone to occur with increasing system reliabilities (Carsten & Martens, 2019; Endsley, 2017). Although ideally the system should only be allowed to be activated under conditions that it can cope with, accidents cannot always be avoided. Another potential issue induced by extensive use of automation is the loss of manual control skills, which has been frequently found among pilots that have become accustomed to autopilot systems (Veillette, 1995; Young, Fanjoy, & Suckow, 2006; Haslbeck & Zhang, 2017). Safety critical situations would occur when the driver has to take over control due to system failures, while he/she is no longer proficient in manual driving.

The human factors challenges described above largely revolve around transitions of control from automation to the driver and vice versa. A good understanding of drivers' performance at control transitions in various states and conditions remains substantial for the development of safe driving automation platforms. In the following section, we introduce the mechanism of control transitions in driving automation, driver take-over process, and the measures for driver take-over performance.

1.4 Control transitions in driving automation

Transitions of driving tasks between the human driver and the automation system may occur at different automation levels, due to various reasons such as drivers' personal preferences, entering or exiting the ODD, sensor limits or in extreme cases malfunctioning This can be further differentiated between transitions of control and transitions of monitoring activity (Lu et al., 2016). A transition of control mainly involves a reallocation of vehicle motion control tasks, while a monitoring transition concerns a change in status between driver (temporarily) monitoring and system (temporarily) monitoring. An overview of all possible transitions is illustrated in Figure 1.2.

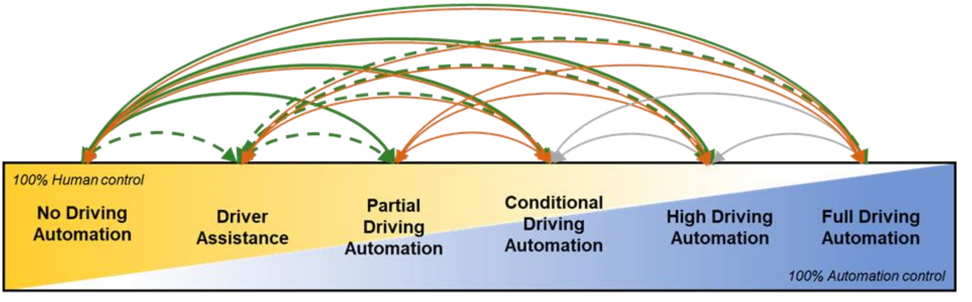

Figure 1.2: All possible transitions between the driver and the automation system at different levels of automation, adapted from Flemisch, Kelsch, Löper, Schieben, & Schindler, (2008) and Lu et al., (2016). The solid green lines indicate transitions of both longitudinal and lateral vehicle motion control; the dashed green lines indicate transitions of vehicle motion control in only one dimension; the orange lines indicate monitoring transitions.

Martens et al., (2008) outlined three fundamental questions to classify control transitions: 1) who has it (who conducts the control task at the start of the transition); 2) who should get it (who should conduct the control task after the transition); and 3) who initiates the transition. Based on this classification scheme, Lu et al., (2016) further integrated the underlying reason of the transition into their framework, (i.e., whether the transition is *mandatory* based on certain decision rules or requirements, or *optional* based on the driver's voluntary intention while both agents are capable of the control task), yielding six types of control transitions between the driver and the automation as depicted in Figure 1.3.

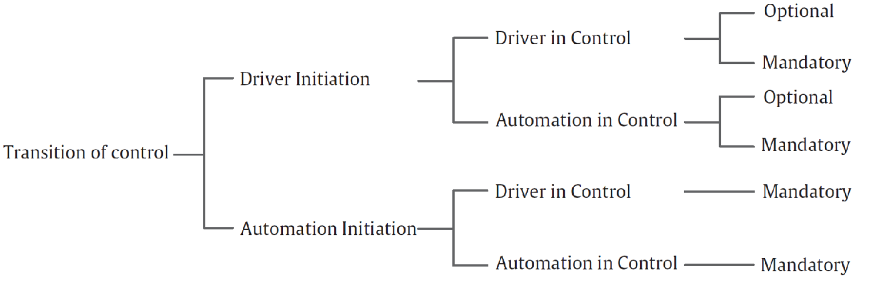

Figure 1.3: Classification tree of transitions of control (Lu et al., 2016).

Control transitions to the automation are normally performed within the ODD of the system. In optional Driver-Initiated transitions, the driver decides to activate the automation system because he/she feels like doing so, such as switch on the ACC on a normal highway. In turn, the driver may choose to deactivate the automation and start driving manually even though the system is functioning well. Mandatory Driver-Initiated transitions concern situations where the driver has to switch on the automation to avoid or minimize undesirable consequences or safely-critical situations. For example, the driver has to activate the automation in order to enter an area specially equipped for automated vehicles, or to join in an automated platoon. Another possible use case is that the driver hands over control to the automation because he/she is no longer able to drive safely (e.g. due to emergency health issues or with driver fatigue). Mandatory transitions to automation could be automatically initiated by the automation system as well, depending on the implemented transition strategies. Currently, these transitions do not exist yet in current levels of automation of commercially available vehicles.

Mandatory control transitions to the driver (also referred to as *driver take-over*) are generally seen as a major challenge facing automotive engineers and human factors researchers, which would occur upon exceeding the system's ODD or due to system failures. In such situations, the driver is forced to take over control because the automation can no longer drive safely or cannot drive safely under conditions that are coming up soon. Safety critical situations would occur if the driver cannot intervene adequately in time.

In Automation-Initiated transitions, the system is able to determine the necessity to transfer control to the driver and issue a TOR, which allows the driver to respond within a certain time budget before causing adverse consequences (e.g., a collision) or triggering the system fallback performance. The available time budget may vary largely between different types of take-over scenarios (Gold, Naujoks, Radlmayr, Bellem, & Jarosch, 2018). If, when or where the system reaches its functional limit can be estimated in advance from system backend, map or V2X communication (i.e., scheduled take-over). Therefore, the system is able to provide a timely TOR with a longer time budget. The take-over scenario is normally more critical when it is related to the behaviours of other road users or system failures (i.e., unscheduled take-over). The available time budget depends on the predictability of the unfolding situation and the capabilities of the onboard sensors.

In Driver-Initiated transitions, the driver diagnoses that the system can no longer handle the current situation based on kinematic feedback from the vehicle, cues in the driving environment and his/her expectations, and takes over control without being requested by the system. This type of transition would occur when the system is not acting according to what a driver expects, or when a system is not able to detect (in time) a critical event or fails to diagnose its malfunction (i.e., silent automation failures, Louw, Kuo, Romano, Radhakrishnan, Lenné, & Merat, 2019), which is more likely in lower levels of driving automation. The hazardous situation could have already become highly critical when it is detected by the driver.

1.4.1 Driver take-over process and take-over performance

As with most of the human executed activities in dynamic environments, taking over control in response to external input involves multiple psychological and motor processes. Referencing Wickens' information processing model (Wickens, Hollands, Banbury, & Parasuraman, 2015), the take-over process covers 1) the detection and perception of the take-over stimulus (i.e., a TOR or an environmental event that can initiate a driver take-over), 2) cognitive processing of the stimulus (to comprehend the necessity to take over control) and the current driving situation (to determine how to take over control), 3) establishment of motor readiness by repositioning the hands on the wheel and foot on the pedal, and 4) execution of an action that influences vehicle motion control (by steering, pressing the braking/gas pedal, or pressing a button to disengage the automation).

Wickens et al. (2015) described speed, accuracy, and attentional demand as “the big three” measures of human performance. Generally speaking, the faster, the more accurately, and the more effortlessly a task is being conducted, the better the performance. Correspondingly, driver take-over performance can be evaluated using measures related to the response time (RT) to complete the take-over process, the quality of the manoeuvre that is required for a specific take-over scenario, as well as the workload involved in the process. They are introduced in turn below.

Take-over time

Driver take-over response time, or in short *take-over time* (TOT), is an essential parameter to evaluate driver take-over performance. A successful take-over first requires the driver to respond before the situation exceeds his/her controllability (Nilsson, Falcone, & Vinter, 2015). TOT is generally measured from the onset of the take-over stimulus (a TOR or an environmental event) until the driver makes a conscious intervention (Gold & Bengler, 2014).

Additional response time metrics can be measured for a sequence of actions to break down the take-over process, in order to analyse driver behaviour at a fine-grained level. An overview of measurable RTs is given in Figure 1.4. In a few studies, *gaze reaction time*, *eyes-on-road time*, and *hands-on wheel time* were registered to reflect the moments when the driver senses the take-over stimulus, starts perceptual and cognitive processing of the driving environment, and establishes motor readiness, respectively (e.g., Gold, Damböck, Lorenz, & Bengler, 2013; Körber, Gold, Lechner, & Bengler, 2016; Feldhütter, Gold, Schneider, & Bengler, 2017). Less commonly registered is the initial start of the driver’s hand movement (Kerschbaum, Omozik, Wagner, Levin, Hermsdörfer, & Bengler, 2017; Kerschbaum, Lorenz, & Bengler, 2015), possibly because time consuming video annotation is needed. RTs measured until the first hand movement provide some insight in the time elapsed until the driver has comprehended the necessity to take over control and starts to regain motor readiness. This is similar to *perception time* in the concept *perception-response time* to analyse drivers’ braking response in the manual driving context (Olson, 1986; Green, 2000). *Movement time*, or *motor response time* (corresponding to the second component of *perception-response time*), can be measured from the start of the movement until the moment when the driver grasps the steering wheel, which reflects the time it takes to execute the actual response to establish motor readiness.

It has to be noted that the RTs above may only apply to the analysis of more basic responses towards the take-over stimulus. How long it takes for the driver to fully comprehend the different aspects of the driving situation and how the process of selecting a specific driving manoeuvre is difficult to observe and determine. These processes may overlap with other information processing stages and may even continue after the start of the manoeuvre. The driver may respond inadequately or even incorrectly if he/she takes over control before acquiring a sufficient level of situation awareness, particularly in complex and critical situations.

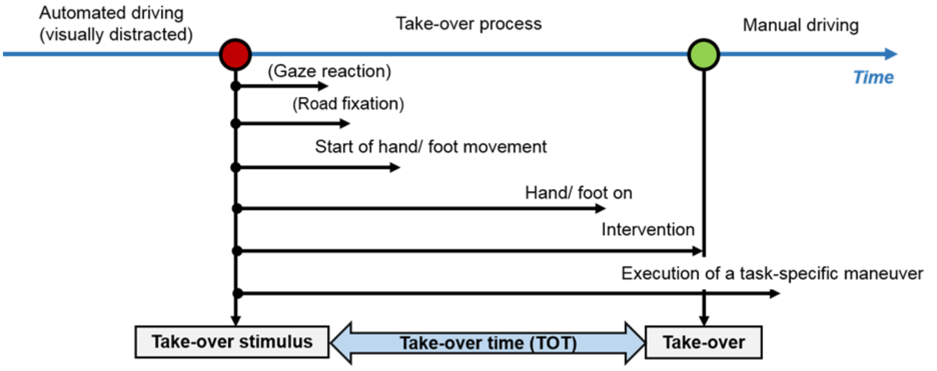

Figure 1.4. Measurable response times (RT) within the take-over process in temporal order, adapted from Gold et al., (2013) with modifications.

Take-over quality

Besides take-over time, the quality of the take-over performance is also important to be measured. The evaluation of take-over quality depends on required actions to handle a certain take-over scenario (Gold et al., 2018; International Organization for Standardization [ISO], 2020). In some simple scenarios, such as taking over at the end of an ODD zone or due to the absence of lane markings, operational actions to stabilise the vehicle in its lane is sufficient. Desired performance is to maintain a steady lane position, a smooth, appropriate speed, and a safe following distance to the front vehicle. Correspondingly, metrics related to the variability of lane position (e.g., Standard Deviation Lane Position, SDLP), steering activity (e.g., the number of steering wheel reversals per minute), driving speed, and time headway can be employed to assess the quality of lateral and longitudinal driving performance. The performance data are often assessed in small windows after the control transition to explore the course of manual driving performance "recovery" as a function of time or travelling distance (Merat, Jamson, Lai, Daly & Carsten, 2014; Skottke, Debus, Wang, & Huestegge, 2014; Pfromm, Khan, Oppelt, Abendroth, & Brudera, 2015; Eriksson & Stanton, 2017). In order to estimate when the carryover effects of automated driving have sufficiently diminished and the driver could continue driving in a safe manner, driving performance after a take-over is often compared to driving performance in a baseline manual driving condition or reference threshold (ISO, 2020). More complex take-over scenarios require the driver to perform tactical manoeuvres according to pre-defined goals or rules, such as lane changing and turning, stopping at a traffic light, and adjusting speed to a new speed limit. These types of scenarios are less addressed in empirical studies. Whether the driver was able to respond correctly and timely to achieve the specific goal is the main criterion used in studies for the assessment of take-over quality.

In most challenging scenarios, the driver has to perform imminent tactical actions to achieve the goal of avoiding a collision with obstacles or other road users. Quality assessment for collision avoidance scenarios mainly concerns if the driver can operate the vehicle in a relatively safe manner and as a minimum can prevent a collision without endangering him or herself and other road users. First it has to be evaluated if crashes or other non-controllable events occur (skidding, rotating, swerving across several lanes or off paved road), which self-evidently would indicate take-over failures (Naujoks, Wiedemanna, Schömig, Jarosch, & Gold, 2018). For successful take-overs, low risk should be involved in the manoeuvre, which can be estimated using surrogate safety metrics such as minimum time to collision (TTC) and minimum clearance towards the obstacle or other road users (Gettman & Head, 2003; Happee, Gold, Radlmayr, Hergeth, & Bengler, 2017; Tarko, 2018). A higher value indicates a larger time gap or spatial safety distance and a lower degree of endangerment (Naujoks et al., 2018). Measures related to acceleration profiles such as maximum longitudinal and lateral acceleration are commonly used to reflect the intensity of the executed manoeuvres. Lower accelerations generally suggest smoother and safer manoeuvring. Both TOT and take-over quality should be taken into consideration to determine take-over performance. While a faster response is generally preferable, it can be assumed that drivers are more prone to making errors. Such a speed-accuracy trade-off (Fitts, 1966; Wickelgren, 1977) in control transitions has been suggested in a number of empirical studies that reported a higher take-over quality when drivers responded later (e.g., Damböck, Weissgerber, Kienle, & Bengler, 2013; Gold et al, 2013; Clark & Feng, 2017; Ito, Takata, & Oosawa, 2016). To find a "sweet spot", balancing take-over quality and TOT is a key aspect in determining a desirable take-over time budget and providing implications for the development of driving automation systems.

Workload

Workload can be understood as the amount of work or effort necessary to perform a task, which concerns both physical and mental aspects (Meijman & Mulder, 1998). When taking over control, the driver experiences physical workload to reposition his/her hands back on the wheel and feet back on the pedals, and mental workload to process the take-over stimulus and the take-over situation, and to make decisions on a take-over action. The physical load would be relatively small, while the mental workload may vary largely depending on task difficulty, situation complexity, and the driver's capability and states (Lee, Regan, & Horrey, 2020).

There are three main categories of workload measurement techniques: subjective measures, physiological measures, and performance measures (De Waard, 1996; O'Donnell & Eggemeier, 1986). Subjective measures assess and quantify personal judgements of experienced workload, which are usually well-established rating scales, such as the NASA-TLX (Task Load Index) (Hart & Staveland, 1988), the SWAT (Subjective Assessment Technique) (Reid & Nygren, 1988), and the RSME (Rating Scale Mental Effort) (Zijlstra & Van Doorn,1985). Physiological measures are used to infer variations in workload through changes in an individual's physiological states. Commonly used measures concern brain activity (EEG), cardiac activity (heart rate, heart rate variability, blood pressure), respiratory activity (respiration rate), eye activity (pupil diameter, eye fixation), and galvanic skin response (De Waard, 1996; Charles & Nixon, 2019). Performance-based measurement techniques are developed based on the assumption that the human operator has limited attentional resources (Kahneman, 1973; Yeh & Wickens, 1988). Decrements in primary task (i.e., the task of interest) performance can be an indicator that the workload is too high or too low, as both overload and underload can diminish performance. The performance on an additional, low-priority task, also called secondary task, can reflect the remaining capacity of the operator while performing the primary task (see e.g., Jahn, Oehme, Krems, & Gelau, 2005; Martens & Winsum, 2001; and Verwey, 2000 for applications of secondary task measures in the manual driving context).

In the context of automated driving, driver workload during the use of automation systems is a frequently recurring research topic (e.g., Stanton, Young, & McCaulder, 1997; Heikoop, De Winter, Van Arem, & Stanton, 2019; Stapel, Mullakkal-Babu, & Happee, 2019; see De Winter, Happee, Martens, & Stanton, 2014 for a review), while workload directly related to control transitions is hardly touched upon. One possible reason is a lack of suitable workload measures. Physiological and performance measures are usually aggregated over time and consequently not applicable for assessing workload in a fragment of seconds (De Waard, 1996; Verwey & Veltman, 1996). They are also likely to interfere with the take-over process involving rapid physical movements. Subjective assessment causes least intrusion, but may induce biases if the driver cannot precisely recall workload experienced during one specific control transition, especially when multiples transitions are performed within one drive. Focusing on safety aspects of control transitions, this thesis will mainly assess time and quality aspects of take-over performance, which are direct indicators of transition safety and can be objectively assessed in simple, and non-intrusive manners.

1.5 Research objectives and research questions

This thesis focusses on Human Factors issues related to the transition of control from SAE L2-L4 vehicle automation to manual control, in both stand-alone automated driving scenarios and automated platooning scenarios. The research in this thesis addresses the challenges of take-over times and take over quality in various conditions. In order to contribute to a better understanding of behaviour during transitions of control to manual driving, the following research objectives are proposed:

- **Obj. 1: Explore determinants of TOT and TOT variability in normal and critical take-over scenarios and gain a deeper insight in the actual driver take-over process.**

The first objective is to study the factors that affect TOT under various circumstances, in order to get more insight in inter- and intra-individual differences. Knowing the factors that affect TOT may help support drivers in taking back control in a safe and smooth manner. Although existing research provides useful insight into some factors that affect TOTs, findings of the individual studies are hardly generalizable across different driving contexts, because only a small number of variables are manipulated per study. Up to now, little effort has been made to quantitatively synthesize all the available TOT studies for a more holistic picture. In addition, most studies only focus on mean or median TOT values without addressing intra- and inter-individual differences (Dinparast, Djadid, Lee, Domeyer, Schwarz, Brown, & Gunaratne, 2019; Eriksson & Stanton, 2017; Mole et al., 2020). Nevertheless, outliers in the response time distribution are most prone to safety critical accidents and other adverse situations (Horrey & Wickens, 2007). This would indicate that taking mean TOT of one study as the basis for understanding how long it takes before a driver takes back control may lead to an unsafe design. More research efforts are needed to focus on variability in TOTs in various conditions, and to investigate the cause for large outliers. Wickens & Corlett (2015) even claim that the ultimate goal is to design safe automation systems that can accommodate as close to 100% of the target driver population.

- **Obj. 2: Study driver take-over time and performance with professional drivers in automated truck platooning scenarios.**

The second objective is to fill in the research gap of TOT in platooning scenarios, particularly that of professional truck drivers. Truck platooning is considered as a first step towards automated freight transportation in an open and uncontrolled environment (Bhoopalam, Agatz, & Zuidwijk, 2018; Janssen, Zwijnenberg, Blankers, & De Kruijff, 2015; World Maritime University, 2019). Nevertheless, the large majority of human factors studies merely focus on passenger car scenarios in a non-platooning situation. Research on professional truck drivers' take-over behaviour is very limited, and at the start of this thesis, we were not aware of any attempts that were made to systematically study driver take-over performance when leaving an automated platoon. It still remains to be understood if the specific features of platooning, such as the very short inter-vehicular distance and blocked front view, and the driver categories (professional or non-professional drivers), influence the way drivers take over control. If we are able to identify the specific requirements of platoon drivers, and the differences between professional truck drivers and normal passenger car drivers in take-over behaviour, we can deliver valuable input for designing safe control transitions in platooning systems.

- **Obj. 3: Explore potential approaches that prime drivers for a safe and smooth take-over.**

The third objective is to design and evaluate solutions that prime drivers for a safe and smooth take-over. As mentioned in the previous sections, a TOR with a large time budget cannot always be provided, particularly in on-road settings where critical yet unpredictable situations may occur. However, it is ineffective and unrealistic to require the driver to sustain attention and stay prepared to take back control throughout the ride. It is important to explore possible countermeasures that adapt to the uncertainty and complexity of the road situations and allow the driver to allocate attention accordingly. As mentioned above (Obj. 1), several previous studies pointed to a large variation between individual drivers in taking over control, and no single take-over time budget exists that fits all situations. The feasibility of an adaptive and personalized control transition approach will also be discussed in this thesis.

Based on the research objectives, the following research questions are formulated:

- **RQ1: What factors influence driver response times in taking back control from automated to manual driving?**

This research question focuses on TOT and mainly links to research **Obj. 1.** To answer this question, a comprehensive literature search and meta-analysis has been conducted to provide the state of the art on driver take-over research, and to explore determinants of TOT on an aggregated level (i.e., what determined the mean/median TOTs). Data collected from empirical driving simulator studies performed in this thesis provide additional insight into influencing factors that were not included in the meta-analysis.

- **RQ2: How do car drivers and professional truck drivers perform when decoupling from highly automated platoons in normal, non-critical situations under the influence of various task conditions?**

This research question focuses on driver behaviour at control transitions in platooning scenarios, and mainly links to research objective 2**.** This question is answered by analysing car and truck drivers' performance data when taking over in car and truck platooning driving simulator studies.

- **RQ3: Could a monitoring request help driver respond more adequately with take-over performance in critical take-over situations?**

This research question focuses on designing and evaluating an innovative HMI concept that may prepare the driver for potential critical takeovers, which mainly links to research **Obj. 3.** To answer this question, an empirical car driving simulator study is conducted that compares drivers' take-over performance and subjective ratings when using the innovative system to the conventional system that only issues TORs.

- **RQ4: What explains variability in driver take-over times and is an adaptive approach tuned to a specific driver or conditions a feasible solution for a safe and smooth transition to manual driving?**

This RQ focuses on variability in TOT between and within drivers (**Obj. 1**), based on which the feasibility of adaptive driving automation tuned to a specific driver's states is discussed (**Obj. 3**). This question is answered combining the meta-review study, from which the correlation between the mean and standard deviation of TOT can be yielded, and all empirical studies performed in this thesis, which allow inspection into individual drivers' takeover response.

This research contributes to the literature on Human Factors in transport, primarily in the domain of highly automated driving in the context of driver behaviour at transitions of control. Especially, this research is one of the initial studies that focuses on automated truck platooning and adaptive automotive automation. The results contribute to the development of an improved human-system interaction for comfortable and safe transitions of control.

1.6 Thesis structure

This thesis consists of eight chapters. The structure of the thesis and the links between the chapters and the research questions are depicted in Figure 1.5, and explained below.

In Chapter 1, the general research background, research objectives and research questions have been introduced.

Chapter 2 presents an exhaustive meta-review of 129 driver take-over time studies. The aim of this meta-review is to provide the state of the art on the relevant research on TOT, and to explore the effects of a wide range of factors on driver TOT and its variability on an aggregated level. This study mainly aims to answer **RQ 1.** Three complementary meta-analytical approaches were employed: (1) a within-study analysis, in which differences in mean TOTs were assessed for pairs of experimental conditions, (2) a between-study analysis, in which correlations between experimental conditions and mean TOTs were assessed, and (3) a linear mixed-effects model combining between study and within-study effects.

Chapter 3, 4, 5 and 6 present empirical studies that systematically investigate driver take-over performance in platooning scenarios. Data for driver performance analyses were generated from three simulator-based studies conducted in the project Adaptive Virtue Tow-Bar (A-VTB) within TNO's Early Research Program Human Enhancement. Chapter 3 and 4 describe two truck platooning studies with professional truck drivers in non-critical scenarios. In Chapter 5, we compared a passenger car platooning study with one truck platooning study to explore the difference between car and truck drivers. Chapter 6 concerns truck drivers' take-over performance in a critical system failure scenario.

The four chapters together provide a holistic picture of drivers' take-over performance in platooning scenarios and address **RQ 2**. In addition, we conducted manual video annotations to break down the total TOT. TOT was divided into the perception response time and the hand movement response, in order to analyse driver take-over processes at a fine-grained level. Video recordings of participants' behaviours during the take-over process were also analysed to explore individual differences. This contributes to a better understanding of the driver take-over process and contributes to **RQ 1**. A more detailed overview of each chapter is presented below.

- Chapter 3 and Chapter 4 describe two truck platooning experiments with professional truck drivers in a truck driving simulator. The aim is to investigate how truck drivers take over control to leave the truck platoon in normal situations under three task conditions: monitoring the driving situation, performing non-driving tasks on a tablet PC, and resting with the eyes closed. The difference between the two experiments lies in whether the tablet PC was hand-held or mounted on the centre console. In both experiments, driver TOTs and take-over quality in terms of vehicle stabilization and responses to an emergency brake event were analysed and compared between task conditions

- Chapter 5 presents a comparison study**.** A car platooning experiment was conducted in which identical experimental designs were used as in the first truck experiment (Chapter 4), but with the driving simulator in car configuration and with 18 passenger car drivers as participants. Car drivers' take-over performance was compared to that of the truck drivers to explore potential differences between two driver types and vehicle types.

- Chapter 6 describes a critical truck platooning scenario in which a system failure occurred and the participants had to take over control within a short time budget. Besides investigating truck drivers' take-over performance in abnormal and emergency situations, this study also explored the effects of a "see-through" screen that was developed in the driving simulation that allowed the driver to obtain images of the road situation in front of the lead vehicle. The see-through screen was simulated as a large LED screen attached at the back of the lead simulated vehicle. For drivers in the truck platoon, monitoring surrounding traffic environment and foreseeing upcoming hazardous situations is very difficult due to very short inter-vehicular distances and consequently a heavily blocked front view. It is therefore meaningful to explore whether providing drivers in a truck platoon with additional visual information of the front view can influence their monitoring pattern and increase awareness for an upcoming event.

Chapter 7 presents an empirical study to evaluate an approach that stimulates a dynamic allocation of monitoring tasks to human and automation, addressing **RQ 3.** First, an HMI concept was designed that provides a monitoring request (MR) when approaching a location where driver take-over may or may not be requested. The MR asked the driver to pause the non-driving task, monitor the traffic environment, and be prepared for a potential take-over. If a critical event was detected, the system provided a take-over request (TOR) as well. The effects of the MR+TOR system were assessed in a driving simulator study with 41 participants by comparing driver take-over performance and gaze behaviour to a conventional system that only issued a TOR. Because only a small portion out of all MRs required an actual driver take-over, an additional analysis was conducted to investigate how drivers' compliance with MRs was associated with previously experienced scenarios. The compliance level was measured based on drivers' eye, hand, and foot preparatory behaviours retrieved from manual video observation.

The empirical studies described in Chapter 3 – 7 also allow a deeper insight into individual drivers' take-over behaviour and performance under various conditions, which complement the knowledge obtained from the meta-review (Chapter 2). All together they answer **RQ 1 and RQ 4.**

Chapter 8 discusses the main research findings, conclusions, implications for practice, and recommendations for further research.

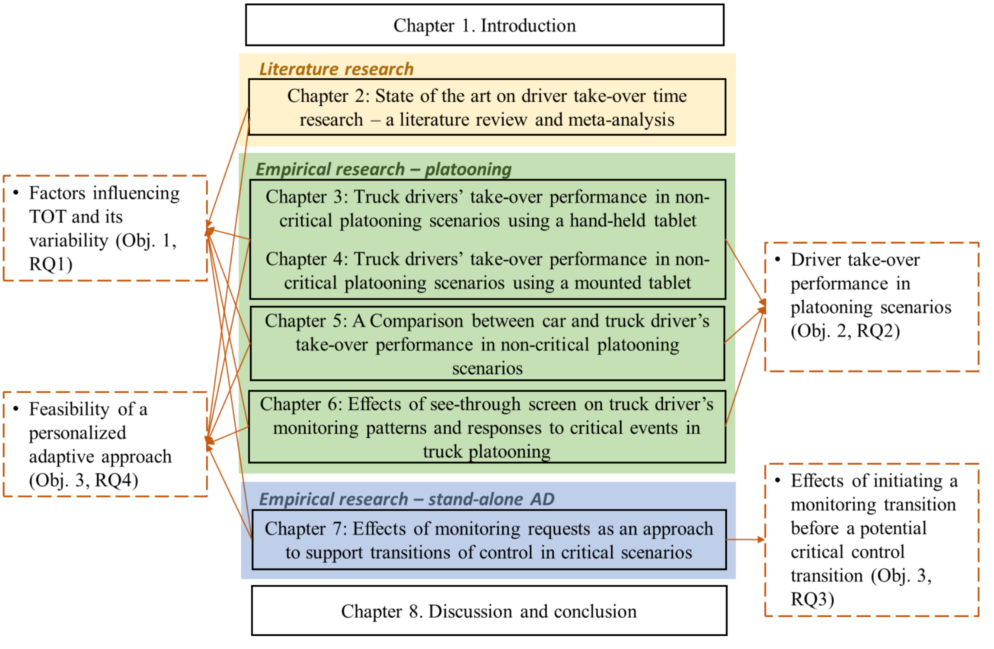

Figure 1.5: Overview of the thesis structure.

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2. Determinants of take-over time from automated driving

This chapter is based on the following publication: Zhang, B., De Winter, J. C. F., Varotto, S., Happee, R., & Martens, M. H (2019). Determinants of take-over time from automated driving: a meta-analysis of 129 studies. *Transportation Research Part F: Traffic Psychology and Behaviour*, *64*, 285–307.

2.1 Introduction

Until automated driving systems are capable of performing all driving tasks under all road conditions (i.e., full automation as defined by SAE International, 2016), drivers will have to take over control when the automation fails or reaches its operational limits. Partial automation (SAE L2), which is already made available by several car manufacturers, requires drivers to monitor the road and to be prepared for immediate intervention at all times. At higher levels of automation (SAE L3 'conditional automation' and L4 'high automation'), drivers are allowed to engage in non-driving activities, while the automation executes the monitoring task and issues a take-over request (TOR) when the driver has to intervene. How long it takes drivers to reclaim manual control and what factors determine take-over time are important questions for both scientific researchers and automobile manufacturers.

2.1.1 Driver take-over process and response times

The driver take-over process comprises several information-processing stages: perception of visual, auditory, and/or vibrotactile stimuli, cognitive processing of the information, response selection (decision making), resuming motor readiness (by repositioning the hands and feet on the steering wheel and pedals), and the actual action (e.g., steering and braking input to the vehicle) (Gold & Bengler, 2014; Gold, Damböck, Lorenz, & Bengler, 2013; Petermeijer, De Winter, & Bengler, 2016; Zeeb, Buchner, & Schrauf, 2015; Zhang, Wilschut, Willemsen, & Martens, 2019). Gold, Damböck et al. (2013) described four response (RT) measures: (1) gaze response time, (2) eyes-on-road time, (3) hands-on-wheel response time, and (4) take-over time (i.e., intervention time). In addition, researchers have used task-specific measures, such as hand movement response time (e.g., Kerschbaum, Lorenz, & Bengler, 2015; Kerschbaum, Omozik, Wagner, Levin, Hermsdörfer, & Bengler, 2017; Zhang et al., 2019), mirror check response time (e.g., Gold, Damböck et al., 2013; Vogelpohl, Kühn, Hummel, Gehlert, & Vollrath, 2018) and lane change response time (e.g., Petermeijer, Cieler, & De Winter, 2017; Eriksson et al., 2019). Although different response time measures can be distinguished, take-over time (TOT), defined as the time that drivers take to resume control from automated driving after a critical event in the environment or after having received a TOR, appears to be the most frequently used measure in the literature.

The temporal sequence of the take-over process is illustrated in Figure 2.1. Typically, the driver has to take over within the 'time budget' available until the system limit of the automation is reached. Such system limits may comprise an upcoming collision (e.g., with a stationary vehicle in the ego lane) or operational limits of the automated driving system (e.g., due to missing lane markings). If drivers do not take over within the available time budget, serious safety issues may occur.

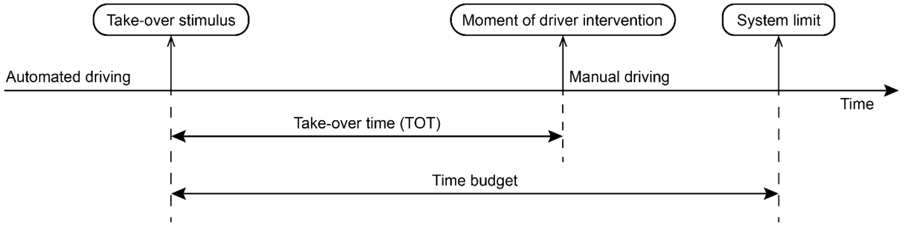

Figure 2.1: Illustration of the take-over procedure. The present meta-analysis focuses on the take-over time (TOT), defined as the time between the take-over stimulus (take-over request or critical event in the environment) and the intervention by the driver.

2.1.2 Previous Review Studies

The empirical literature reports a wide range of TOT values. For example, De Winter, Stanton, Price, and Mistry (2016) reported a mean TOT of 0.87 s (SD = 0.24 s) when the participants were required to brake in response to a salient red stop sign, whereas, in Politis et al. (2018), participants took over control on average 19.8 s (SD = 9.3 s) after the onset of a 60 s countdown TOR.

Several researchers have provided narrative reviews of TOT studies. Radlmayr and Bengler (2015) summarised eleven studies that investigated the effect of take-over time budget and concluded that longer time budgets are associated with longer TOTs and better take-over quality. A time budget smaller than 7 s was regarded as insufficient for a fully distracted driver to successfully take over control. Vogelpohl, Vollrath, Kühn, Hummel, and Gehlert (2016) provided an overview of 22 TOT studies involving a transition from highly automated driving (SAE L3) to manual driving and identified potentially influential factors related to the environment, the driver, the human-machine interface, and the vehicle. The authors suggested that the complexity of the take-over situation, the modality of the TOR, and the non-driving task (NDT) performed at the moment of the TOR are important factors. Furthermore, a traffic situation of high complexity and engagement in NDTs were argued to lead to slow responses, whereas multi-modal TORs shortened the TOT and improved the take-over quality. In another literature survey, Walch et al. (2017) discussed 17 take-over studies, focusing on the effect of the time budget, traffic complexity, NDT, and driver age. The authors concluded that 10 s seems an adequate time budget, while pointing out that the driver state and situational circumstances affect the driver's ability to take over control. Vogelpohl et al. (2016) and Walch et al. (2017) both noted that outcomes were sometimes inconsistent between the surveyed studies. For example, it was observed that Gold, Berisha, and Bengler (2015) and Petermann-Stock, Hackenberg, Muhr, and Mergl (2013) reported significantly longer TOTs when the participants were engaged in visual-motor NDTs compared to cognitive-auditory NDTs, whereas this effect was not statistically significant in the experiment by Radlmayr, Gold, Lorenz, Farid, and Bengler (2014). Another example of an inconsistency is that a negative effect of higher traffic complexity on TOT was found in Radlmayr et al. (2014) and Gold, Lorenz, and Bengler (2014), but not in Shen and Neyens (2014). This heterogeneity suggests that a larger number of studies need to be reviewed to draw reliable conclusions.

Although a number of narrative reviews exist, little effort has been devoted to quantitatively synthesising the available TOT studies. Eriksson and Stanton (2017) reviewed 25 take-over studies; they extracted 43 take-over time budgets (lead times) which varied between 0 and 30 s (mean = 6.37, SD = 5.36 s), and 87 TOTs from 1.14 s to 15 s (mean = 2.96, SD = 1.96 s). The authors noted that 3 s, 4 s, 6 s, and 7 s were the most frequently used time budgets and that the corresponding mean TOTs were 1.14, 2.05, 2.69, and 3.04 s. Apart from the time budget, Eriksson and Stanton (2017) did not review the effect of study variables that may affect the TOT. Gold, Happee, and Bengler (2018) provided a predictive model of TOTs based on the datasets obtained from six driving simulator experiments. Out of the seven variables considered in the model, the time budget, traffic density, and repetition (i.e., prior experience) turned out to be significant predictors, whereas driver age, physical and cognitive load of NDT, and the lane in which the ego car was driving (i.e., left, right, or middle) showed only minor effects. A limitation of Gold, Bengler et al. (2018) is that only six experiments were analysed and that the experimental settings were similar (i.e., in all the experiments, the take-over scenario was represented by two crashed vehicles blocking the ego lane).

The above reviews suggest that the time budget potentially affects TOTs. However, the existing reviews have several limitations. First, the available reviews analysed only a small number of study variables. Second, most reviews did not numerically synthesise the effects of study variables. Third, the number of reviewed studies is small: The maximum number of studies reviewed was 25 (Eriksson & Stanton, 2017), while this study included 129 TOT studies.

2.1.3 Research Objectives

As pointed out above, there is a need for a new quantitative synthesis of the various TOT studies, having a higher statistical power (i.e., a larger number of included studies) and broader scope (i.e., multiple variables examined simultaneously) as compared to previous reviews. We conducted a comprehensive search of empirical studies and employed meta-analytic methods to examine the predictors of TOT.

Cronbach (1975) discussed two disciplines of scientific psychology: experimental psychology, which is concerned with studying the effects of experimental manipulations, and correlational psychology, which is concerned with understanding differences between individuals and groups. In his work, Cronbach called for combining these two disciplines. A similar approach was followed in the present paper.

First, a within-study meta-analysis was performed to summarise studies that compared pairs of experimental conditions. The within-study analysis describes how mean TOTs are affected by a particular study variable when holding all other study variables constant, thus allowing for statements about causal effects.

Second, because individual experiments typically manipulate only a small number of variables, while experimental conditions differ across studies, we also examined the associations between experimental conditions and TOTs. The second approach concerned a correlation analysis to examine the relationships between the mean TOTs and a comprehensive list of study variables (related to the driver, the automation system, the human-machine interface, the take-over situation, and the experimental set-up) across all studies. The between-study analysis allows for predicting under which experimental conditions the mean TOTs will be low or high.

Third, the within-study experimental approach and the between-study correlational approach were united in a linear mixed-effects model. The mixed model allows for a powerful analysis of the effects of study variables while controlling for the confounding effect of the other study variables.

At the end of the paper, we discuss the similarity in the outcomes of the three methods. Consistent results across all three methods suggest high robustness and generalizability.

2.2 Methods

This study was performed in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines (Moher, Liberati, Tetzlaff, & Altman, 2009). No protocol was generated or registered.

2.2.1 Information sources and search strategy

We conducted a literature search with the aim to retrieve as many take-over studies as possible, including grey literature records to minimize publication bias (Rothstein, Sutton, & Borenstein, 2005). Multiple search strategies were used, such as database searching (Google Scholar, ResearchGate), scanning the reference lists of papers, using the 'cited by' feature of Google Scholar, snowballing strategies (Jalali & Wohlin, 2012), and asking fellow researchers for relevant studies. Most searches were conducted using Google Scholar, as it is the most comprehensive search engine, especially for works of the 21st century (De Winter et al., 2014; Martín-Martín et al., 2018). Typically used keywords were 'takeover', 'take over', and 'transition of control' in combination with domain-specific keywords, to minimize false positives (e.g., 'automated driving', 'driverless', or the names of often-cited authors such as 'Bengler' or 'Merat'). The searches were performed between October 2, 2016 and December 17, 2018.

2.2.2 Eligibility criteria

To be included in this review, studies had to fulfil the following six criteria:

1. The study had to involve a transition from partially, conditionally, or highly automated driving (i.e., SAE L2 and above; hands off the steering wheel and feet off the pedals) to manual driving.
2. The study had to involve an automation-to-manual take-over performed by a human (e.g., braking, steering, button pressing).
3. The study had to involve a transition in response to a TOR or a critical event in the environment. That is, this meta-analysis includes only 'mandatory driver-in-control (DC) transitions' as defined by Lu, Happee, Cabrall, Kyriakidis, and De Winter (2016). Studies in which more than one take-over stimulus (i.e., both a TOR and a critical event in the environment) was presented at different moments were not included, because in such cases it cannot be determined to which stimulus the participants responded. For example, in Körber, Baseler, and Bengler (2018), the obstacle was visible three seconds before the TOR, and the drivers were, therefore, able to take over control before the TOR.
4. The study had to report a mean or median take-over time (TOT), or the mean/median TOT should be calculable from the information reported.
5. In the text of the paper, the TOT had to be defined as the time interval between the initiation of the take-over stimulus (i.e., the onset of the TOR or the start of an environmental event that can initiate driver take-over) and the moment of driver intervention (by means of braking, steering, or button pressing).
6. The study had to be written in English or German.

All types of studies were eligible, including journal publications, papers from conference proceedings, theses, reports, posters, and presentation slides. If a publication contained more than one experiment, we considered each experiment as a separate study. We applied no restriction on the year of publication.

2.2.3 Study selection and data extraction

After initial scanning and filtering, we retrieved 299 potentially relevant full-text records, which were further reviewed for eligibility. After removing 30 duplicate records and 1 record written in a language other than English or German (Japanese), 149 records were excluded for the following reasons: no TOT was measured (103 records), no mean/median TOT was reported (8 records), TOT was not defined according to the fifth eligibility criterion or the TOT measurement was not clearly described (18 records), participants were required to have at least one hand on the wheel during automated driving (4 records), or multiple take-over stimuli were presented at different moments (16 records). In the end, 129 studies from 119 records met the inclusion criteria. These studies comprised 520 mean or median TOT observations. In studies where mean TOT values were only available in figures, the numerical values were extracted using the online tool WebPlotDigitizer (Rohatgi, 2017). Besides the mean and median TOT, which are measures of central tendency and our primary meta-analysis outcome of interest (see Section 2.1.1), we also extracted the standard deviation of the TOT as an index of variability.

The data extraction and variable coding (described in Section 2.2.4.2) were conducted by the first author. The second author supervised the process using a file hosting service (Dropbox), conducted multiple manual inspections of the annotated values, and corrected errors.

Ten of the included studies reported no mean TOT, but only the median TOT. Since the distribution of human response times is right skewed, using unadjusted medians together with means would induce bias. To reduce this bias, we applied a multiplication factor of 1.123 to the median TOTs to obtain an estimate of the corresponding mean TOTs. This correction factor was established from the means and medians from 14 included studies in which both values were reported.

An examination of the included studies showed similar experimental methods. That is, almost all studies used a virtual driving simulator and measured the TOT from the simulator sensor data (i.e., brake pedal depression or steering wheel angle). Although the studies involved simulators of different fidelity levels (e.g., motion base vs. no motion base), different experimental designs (e.g., between-subjects vs. within-subjects), and different experimental protocols (in terms of e.g., participant training, instruction, duration, and breaks), these differences provided no meaningful basis for assessing the study quality. Hence, we did not code the quality of individual studies and considered them of equal importance.

Furthermore, we did not apply weights that depend on sample size (e.g., Hedges & Vevea, 1998; Schmidt & Hunter, 2015). A preliminary analysis showed a substantial skewness of the sample size distribution, with a few large-sample studies including over 100 participants and many moderate-sample studies of about 20 participants. The use of unit weights has been recommended when the sample sizes are unequal, to avoid that the meta-analysis outcome is dominated by a small number of large-sample studies (Osburn & Callender, 1992). Our choice for unit weights is in line with simulation studies showing that unit weights offer similar or sometimes even superior predictive validity as compared to procedures that involve weighting (Bobko, Roth, & Buster, 2007; Einhorn & Hogarth, 1975). Unit weights are not estimated from the data and therefore do not have standard errors, as a result of which they can contribute to reduced estimation error as compared to a weighted average, especially when sample sizes and effect sizes are unequal (Bonett, 2008; Einhorn & Hogarth, 1975).

2.2.4 Analysis methods

2.2.4.1 Within-study analysis

In the within-study analysis, pairs of experimental conditions were categorised (e.g., no NDT vs. NDT, young participants vs. old participants, etc.). A meta-analysis was performed for a category when at least four studies were available in that category, following the recommendation by Fu et al. (2011). The 21 identified categories are shown in Figure 2.3.

Because all studies used the same unit to measure TOTs (seconds), the meta-analyses were performed on the raw (unstandardized) difference between mean TOTs (D). The use of Ds allows for intuitive interpretations as compared to standardised effect size measures (Bond, Wiitala, & Richard, 2003; Higgins & Green, 2005). In other words, we described the effect of an independent variable in seconds instead of a dimensionless index such as Cohen’s d. The use of seconds as a unit allows for easy interpretation in regard to practical applications (e.g., time budgets, look-ahead time of sensors) and the scientific literature in general (e.g., literature about brake response times, psychometric literature about reaction times).

The outcome of the meta-analysis was the unweighted average D per category. An absolute average D of 1 s was interpreted as a strong effect, and an absolute average D of 0.5 s was interpreted as a moderate effect.

In addition, we examined whether the D values differ from 0 (i.e., no effect), using a two-sided Wilcoxon signed-rank test with an alpha value of 0.05. This statistical test is conservative, because a significant effect ($p < 0.05$) can only be obtained when six or more studies (D values) are available (i.e., $2 * 0.56 = 0.031 < 0.05$).

2.2.4.2 Between-study analysis

In the between-study analysis, we examined the correlations between 18 study variables (Table 2.1) and the mean TOTs. The 18 selected study variables were related to the driver, the automation system, the human-machine interface, the take-over situation, and the experimental set-up. More specifically, the variables concerned the mean age of participants, simulator fidelity, the level of automation, the modality of the TOR, the non-driving task (the modality of the task and if a device needed to be held in the hands), and the take-over situation (urgency of the scenario, complexity of the required driver response, and interaction with other road users). The selection of the study variables was based on the narrative reviews introduced above, studies providing guidelines for human factors research in the automated driving domain (e.g., De Winter, Happee, Martens, & Stanton, 2014; Gold, Naujoks, Radlmayr, Bellem, & Jarosch, 2018; Naujoks, Befelein, Wiedemann, & Neukum, 2017), and previous studies concerning driver response times in manual driving (e.g., Green, 2000; Summala, 2000). These variables were also selected based on whether they were available from the papers. For example, the physical intensity of the TOR, the level of drowsiness of the driver, and the duration of automated driving were not included as study variables, because these variables were often not documented, even though they are likely to affect the mean TOT.

We used Pearson product-moment correlations (equivalent to point-biserial correlations if the study variable is binary) and Spearman rank-order correlations to describe the relationships between the mean TOT and the study variables. The Spearman rank-order correlation is robust to tailed distributions and outliers.

A standard technique for assessing publication bias is to create a scatter plot showing the study outcome measures on the x-axis and a measure of sample size or precision on the y-axis, also called a funnel plot. An asymmetric relationship, where there exists a correlation between sample size and outcome measure, can be indicative of publication bias (Begg & Mazumdar, 1994; Egger, Smith, Schneider, & Minder, 1997; Deeks, Macaskill, & Irwig, 2005). We expected no effects of publication bias regarding the mean TOT, as high and low TOTs could be regarded as equally interesting to authors, publishers, and editors. Nonetheless, we assessed whether the mean TOT was correlated with the corresponding sample size.

Additionally, we computed correlations between sample size and all study variables (Table 2.1). These correlations allowed us to determine whether larger studies were associated with specific types of study design.

Table 2.1: Study variables and coding

Study variable	Coding	Description
1. Age (AGE)	Years	Mean age of the participant group.
2. Level of automated driving (LAD)	0 = L2; 1 = L3 and above	The level of automated driving (SAE International, 2016) as reported by the authors of the paper. In L2 automated driving, participants are in charge of the monitoring task. In L3 automated driving and above, the drivers are not supposed to monitor the driving environment.
3. Simulator (SIM)[1]	0 = low fidelity	A desktop-based simulator or a simulator providing the environment through computer monitors.
	1 = medium fidelity	An instrumented-cabin simulator or a simulator providing more than 120 deg horizontal field of view.
	2 = high fidelity	A simulator with motion platform or a real car.
4. Visual TOR (TOR_V)	0 = no; 1 = yes	Whether the TOR contains a visual stimulus.
5. Auditory TOR (TOR_A)	0 = no; 1 = yes	Whether the TOR contains an auditory stimulus. We applied no differentiation between vocal and acoustic TORs.
6. Vibrotactile TOR (TOR_VT)	0 = no; 1 = yes	Whether the TOR contains a vibrotactile stimulus (i.e., vibrations are provided on one or more locations on the human body).
7. Presence of TOR (TOR_P)	0 = no; 1 = yes	Whether a TOR is implemented.
8. Visual NDT (NDT_V)	0 = no; 1 yes	Whether the NDT is visual (e.g., reading, watching a movie).
9. Auditory NDT (NDT_A)	0 = no; 1 = yes	Whether the NDT is auditory (e.g., listening to the radio, watching movies with sound, communicating with the instructors and answering questions verbally).
10. Motoric NDT (NDT_M)	0 = no; 1 = yes	Whether dynamic operation by hand is needed to perform the NDT (e.g., texting and tapping).
11. Cognitive load (NDT_C)	0 = normal cognitive load; 1 = high cognitive load	NDTs that require working memory (e.g., N-back task) were assigned to the high cognitive load category. Otherwise, the task was assumed to involve normal cognitive load.
12. Hand holding a device (HAND)	0 = hands-free (No non-driving task, the non-driving task does not require a device, or the non-driving task is performed using a fixed device);	Whether a device is handheld when undertaking the non-driving task.

	1 = handheld	
13. Presence of a non-driving task (NDT_P)	0 = no; 1 = yes	Whether a non-driving task is performed.
14. Time budget to collision (TBTC)[1]	Ratio variable	The available time budget for a response from the initiation of the take-over stimulus until the collision with an obstacle.
15. Time budget to other boundaries (TBTB)[1]	Ratio variable	The time from the initiation of the take-over stimulus until reaching the boundaries of the automated driving system other than collisions (e.g., due to the end of the automated zone, missing lane markers, or system failure).
16. Urgency (URG)[1]	0 = low urgency	No foreseeable collision risk or a high time budget to collision (≥ 15 s).
	1 = medium urgency	Potential collision risk or disturbance to other road users if no response was made (e.g., the ego car drifting to the adjacent lane containing traffic), or a medium time budget (between 8 s and 15 s).
	2 = high urgency	Immediate risk of collision (time budget ≤ 8 s) if no response was made, or the participants were instructed to react to a stimulus as quickly as possible.
17. Driver response (DRE)[1]	1 = low complexity	The participant had to take over control on a straight road by stabilising the vehicle in its lane.
	2 = medium complexity	The take-over scenarios required a specific driver response (braking or steering), such as when encountering a road narrowing, road constructions, or decelerating vehicles ahead, or when having to take over control on a curvy road.
	3 = high complexity	The take-over scenario requires complex driver decision making. The participant had to decide whether to brake or steer in response to the event.
18. Interaction with other road users (IRU)	0 = no	There were no other road users around, or other road users could not affect the driver's decision-making.
	1 = yes	The participants had to take into account one or more other road users when choosing their optimal take-over action. For example, participants had to take over control while driving in the middle lane while the left lane contained traffic.

[1]*Note.* The fidelity of the simulator was identified according to De Winter et al. (2014). The classification of URG and DRE was adapted from Gold, Naujoks et al. (2018). URG combines the TBTC and TBTB variables. TOR = Take-over request, NDT = Non-driving task.

2.2.4.3 Linear mixed-effects model

We estimated a linear mixed-effects model describing the impact of the study variables on the mean TOTs, using the same dataset as the between-study analysis. A study-specific error term ϑ was introduced to capture unobserved effects that affect mean TOTs within a study (i.e., the intercept differs between studies).

The model was estimated using the 'Mixed Model' command in SPSS 24 (IBM Corporation, 2016) with the estimation method restricted maximum-likelihood (REML) (Molenberghs, Kenward, & Verbeke, 2009; Zuur, Leno, Walker, Saveliev, & Smith, 2009). Goodness-of-fit measures (log likelihood) and information criteria (AIC, BIC) were used to compare alternative model specifications. The SPSS script is provided in the supplementary materials.

A log-normal probability density function was found to fit the mean TOT distribution better than the normal probability density function. All variables listed in Table 2.1 were tested as potential explanatory factors. The variables included in the final specification were selected based on their meaning (i.e., we selected non-redundant variables) and statistical significance ($p < 0.05$). One parameter was associated with each level of the explanatory variables and differences between levels were tested comparing alternative model specifications. Levels that did not differ significantly were merged. Variables that had a non-significant impact on the mean TOTs were excluded one by one. When a variable could not be extracted from one or more studies, a dummy variable was created to indicate the missing values. This variable was included in the model equation in addition to the original variable (dummy variable adjustment method). The advantage of this approach is that all observations could be analysed.

2.3 Results

2.3.1 Study characteristics

The 129 included studies yielded 520 mean TOT observations from 4556 participants. 45 studies were conducted in a high-fidelity driving simulator with motion platform (40 studies) or in a real car (five studies). The 129 studies comprised 68 papers from conference proceedings, 40 journals articles, 3 technical reports, 16 chapters from a PhD or master thesis, and 2 posters. The year of publication ranged between 2000 and 2018, with the majority of the studies being published in and after 2015 (116 out of 129). A list of the included studies, the scores per study variable, and a MATLAB script that processes these data are provided in the supplementary materials.

The mean TOT across studies and conditions ranged from 0.69 s to 19.79 s, and the average mean TOT was 2.72 s ($SD = 1.45$, $n = 520$). Figure 2.2 shows the distribution of the mean TOTs, which is right-skewed.

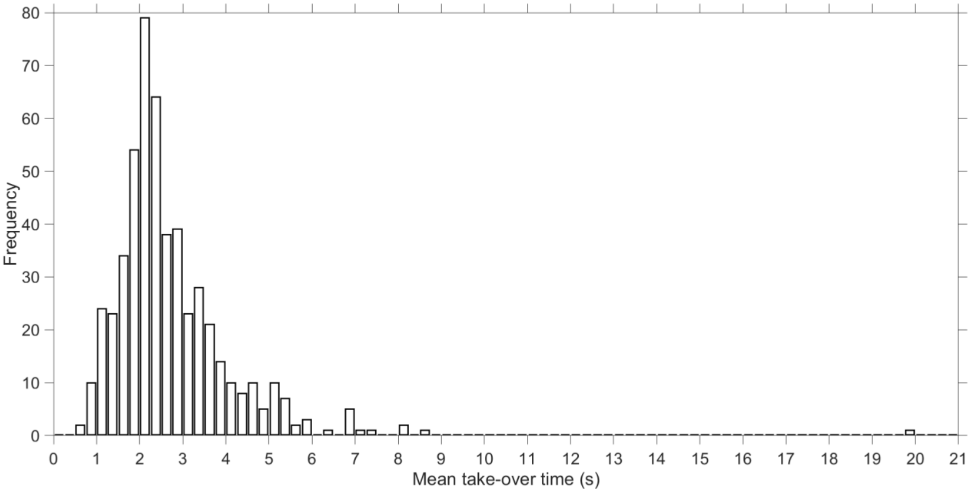

Figure 2.2: Distribution of 520 mean take-over times (TOTs) reported in the included studies. The bin width is 0.25 s.

2.3.2 Within-study analysis

Twenty-one categories with four or more studies were identified in the experimental analysis. Figure 2.3 shows the average difference in mean TOTs (D) for each category (squares), as well as the Ds from each study (smaller circles). The presence of non-driving tasks and the modality of the take-over request (TOR) were frequently used independent variables.

The following statistically significant findings stand out from Figure 2.3:

- A strong effect of time budget was found, with a higher mean TOT (average D = 1.35 s) for a large time budget compared to a small time budget.
- The mean TOT was substantially lower when taking over control for the second time (when asked to take over twice in the same driving session or perform the same scenario in a second driving session) compared to the first time (average D = -1.00 s).
- The use of a handheld device strongly increased the mean TOT (average D = 1.33 s).
- For hands-free non-driving tasks, performing a visual non-driving task slightly increased the mean TOT compared to not performing a non-driving task (average D = 0.29 s).
- The presentation of a TOR moderately decreased response times compared to when no TOR was provided (average D = -0.58 s).

In addition, the following findings are noteworthy, although based on five or less studies.

- Having eyes closed before taking over control strongly increased TOTs compared to not performing a non-driving task and staying alert (average D = 1.19 s).
- Strongly reduced TOTs were found when an auditory or vibrotactile TOR was provided compared to a visual-only TOR (average D = -1.41 and -1.41 s, respectively).
- Being able to anticipate the TOR (e.g., when the TOR was periodically scheduled or could be anticipated from environmental cues such as the traffic and weather) moderately shortened the mean TOT (average D = -0.54 s).
- The effect of traffic compared to no traffic was moderate (average D = 0.49 s).

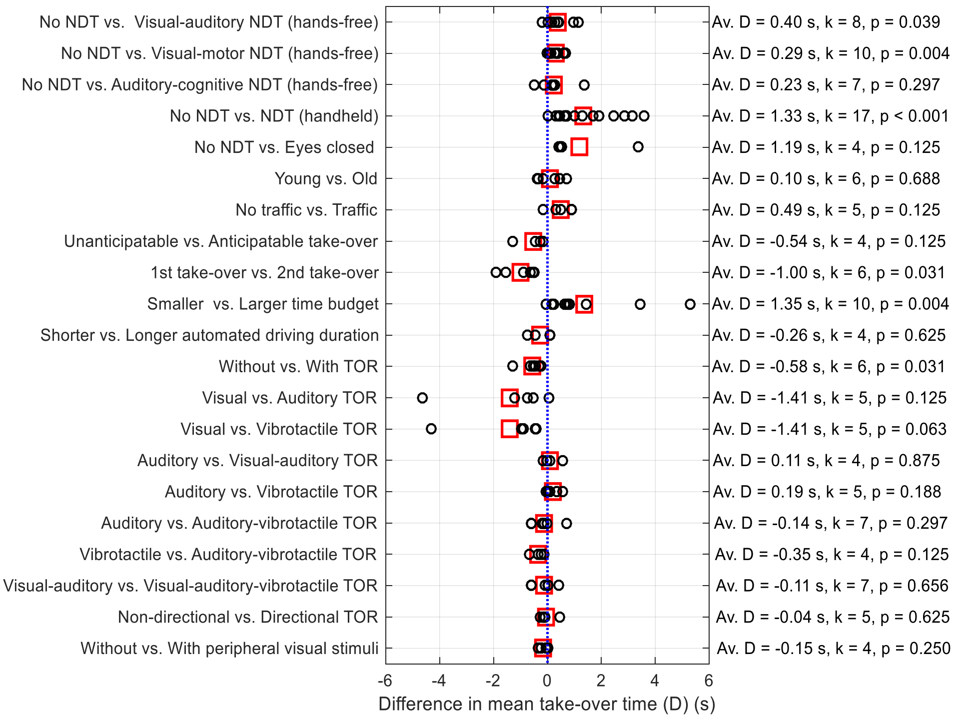

Figure 2.3: Within-study effects. The circles represent the difference in mean take-over time between two conditions (D) of a particular study. A positive D indicates that a larger mean TOT was obtained from the latter condition compared to the former condition. The large square markers represent the average D in the category. k represents the number of studies (D values) in the category. p is the p-value from a two-sided signed rank test for the hypothesis that the D values come from a distribution having a median of 0. TOR = Take-over request, NDT = Non-driving task. A directional TOR is a TOR that is informative about the location of the hazard. Peripheral visual stimuli are stimuli that indicate the status of the automation or the environment (e.g., using ambient LEDs).

2.3.3 Between-study analysis

The correlations between the 18 study variables and the mean TOT are shown in Table 2.2. As in the within-study analysis, urgency of the take-over scenario and holding a handheld device showed strong correlations with the mean TOT: higher-urgency levels and shorter time budgets were associated with lower mean TOT (URG: $r = -.44$; $\rho = -.42$; TBTC: $r = .53$, $\rho = .43$; TBTB: $r = .73$, $\rho = .31$), and holding a handheld device (HAND) yielded higher mean TOT ($r = .30$, $\rho = .35$). The correlations between mean TOT and other categorical variables were weak to moderate, with absolute values below 0.3. That is, the mean TOT did not substantially correlate with the modality of the TOR or the type of non-driving task.

Table 2.2: Correlations between the study variables and mean TOTs in the between-study analysis. Both Pearson product-moment correlations (r) and Spearman rank-order correlations (ρ) are reported.

Study variable	Correlation with mean TOT					
	r	ρ	Study variable conditions	n	Average mean TOT (s)	SD mean TOT (s)
1. AGE	.22	.24	-	485	-	-
2. SIM	-.04	.02	0 (low fidelity)	81	2.67	2.39
			1 (medium fidelity)	268	2.84	1.33
			2 (high fidelity)	171	2.57	0.95
3. LAD	.15	.19	0 (L2)	62	2.14	1.17
			1 (L3 and above)	458	2.80	1.47
4. TOR_V	.04	.08	0 (no visual TOR)	160	2.63	1.75
			1 (with visual TOR)	360	2.77	1.29
5. TOR_A	.12	.12	0 (no auditory TOR)	84	2.33	1.00
			1 (with auditory TOR)	436	2.80	1.51
6. TOR_VT	-.11	-.10	0 (no vibrotactile TOR)	447	2.79	1.50
			1 (with vibrotactile TOR)	73	2.35	0.99
7. TOR_P	.06	.06	0 (no TOR)	34	2.40	1.08
			1 (TOR present)	486	2.75	1.47
8. NDT_V	.13	.13	0 (no visual NDT)	204	2.49	1.12
			1 (the NDT is visual)	309	2.89	1.62
9. NDT_A	-.03	-.07	0 (no auditory NDT)	384	2.75	1.29
			1 (the NDT is auditory)	129	2.67	1.88
10. NDT_M	-.01	-.04	0 (no motoric NDT)	289	2.74	1.27
			1 (the NDT requires a motoric manoeuvre)	224	2.72	1.67
11. NDT_C	-.05	-.11	0 (without highly cognitively demanding NDT)	385	2.78	1.28
			1 (with highly cognitively demanding NDT)	128	2.60	1.90
12. HAND	.30	.35	0 (no handheld device)	371	2.54	1.42
			1 (NDT device held in the hands)	108	3.61	1.46
13. NDT_P	.11	.11	0 (no NDT present at the moment of TOR)	143	2.46	1.17
			1 (NDT present at the moment of TOR)	377	2.82	1.53
14. URG	-.44	-.42	0 (low urgency)	83	3.95	2.35
			1 (medium urgency)	114	3.03	1.32
			2 (high urgency)	295	2.25	0.81
15. DRE	-.16	-.07	0 (low response complexity)	108	3.43	2.21
			1 (medium response complexity)	134	2.34	1.16
			2 (high response complexity)	253	2.66	1.04
16. IRU	.08	.14	0 (no interaction with other road user)	344	2.67	1.55
			1 (interaction with other road user)	141	2.93	1.24
17. TBTC	.53	.43	—	240	—	—
18. TBTB	.73	.31	—	160	—	—

Note. TOR = Take-over request, NDT = Non-driving task.

Additionally, we calculated the correlation between the mean and the standard deviation of the TOTs and found a strong association (Figure 2.4; $r = .82$; $\rho = .73$, $n = 397$). The correlations between the mean TOTs and the three continuous study variables: AGE, TBTC, and TBTB are depicted in Figure 2.5.

A weak to moderate correlation was observed between sample size and mean TOT ($r = .21$, $\rho = .14$, $n = 520$), see Figure 2.6. The correlations between sample size and all study variables were weak with an absolute r and ρ smaller than 0.20, except for the correlation with the time budget to collision (TBTC, $r = .26$, $\rho = 27$, $n = 240$) and simulator fidelity where ρ was smaller than -0.20 (SIM; $r = -.13$, $\rho = -.25$, $n = 520$). In other words, studies in high-fidelity simulators involved smaller sample sizes than studies in low-fidelity simulators.

Table 2.3 shows the correlations between the study variables, providing insight into the patterns of the experimental design. For a higher level of automation, the studies tended to implement a TOR ($\rho = .65$), instruct the participants to perform a non-driving task ($\rho = 0.34$), and provide longer time budgets to collision ($\rho = .35$). These observations are in accordance with the definition of SAE International (2016).

Concerning the modalities of the non-driving task and TOR, strong positive correlations were found between the presence of a motoric and visual non-driving task ($\rho = 0.68$). Visual and auditory TORs tended to be combined ($\rho = 0.35$), which was not the case for the auditory and vibrotactile modalities ($\rho = -0.35$).

A complex driver response was more likely to be required when the take-over situation was more urgent ($\rho = 0.52$), and when other road users were involved in the take-over process ($\rho = 0.46$). Also, it is worth noting that studies that used higher fidelity simulators tended to employ older participants ($\rho = 0.38$).

Table 2.3: Spearman-order rank correlations (ρ) between the predictor variables shown in Table 2.2.

	1. AGE	2. SIM	3. LAD	4. TOR_V	5. TOR_A	6. TOR_VT	7. TOR_P	8. NDT_V	9. NDT_A	10. NDT_M	11. NDT_C	12. HAND	13. NDT_P	14. URG	15. DRE	16. IRU	17. TBTC	18. TBTB
1.AGE	-																	
2.SIM	.38	-																
3.LAD	-.07	.03	-															
4.TOR_V	.07	.26	.24	-														
5.TOR_A	.18	.18	.34	.35	-													
6.TOR_VT	-.21	-.30	.13	-.13	-.35	-												
7.TOR_P	.05	.08	.65	.40	.60	.11	-											
8.NDT_V	-.12	-.08	.30	.12	.08	.10	.19	-										
9.NDT_A	.04	-.17	.08	-.09	-.04	.07	.04	.03	-									
10.NDT_M	-.18	-.01	.28	.13	.07	.13	.18	.68	-.21	-								
11.NDT_C	-.09	-.21	.16	-.06	.01	.09	.10	.13	.27	.29	-							
12.HAND	-.05	.03	.21	.09	.10	.04	.11	.31	-.14	.24	-.12	-						
13.NDT_P	-.08	-.08	.34	.08	.08	.11	.22	.77	.36	.55	.33	.35	-					
14.URG	-.27	.01	-.16	-.04	-.14	.10	-.13	-.07	-.02	.12	.13	-.18	-.06	-				
15.DRE	-.10	.05	.06	.00	-.01	.09	-.01	.05	-.04	.17	.10	.00	.09	.52	-			
16.IRU	.12	.03	.08	.03	.01	-.06	.00	.01	-.07	.05	.16	.04	.02	.10	.46	-		
17.TBTC	-.17	-.30	.35	.13	.02	.20	.22	.09	.01	.02	-.03	.21	.17	-.61	-.12	-.01	-	
18.TBTB	-.24	.08	.22	-.19	-.12	.13	.01	.12	-.03	.21	-.06	.28	.16	-.33	.03	-.01	N/A	-

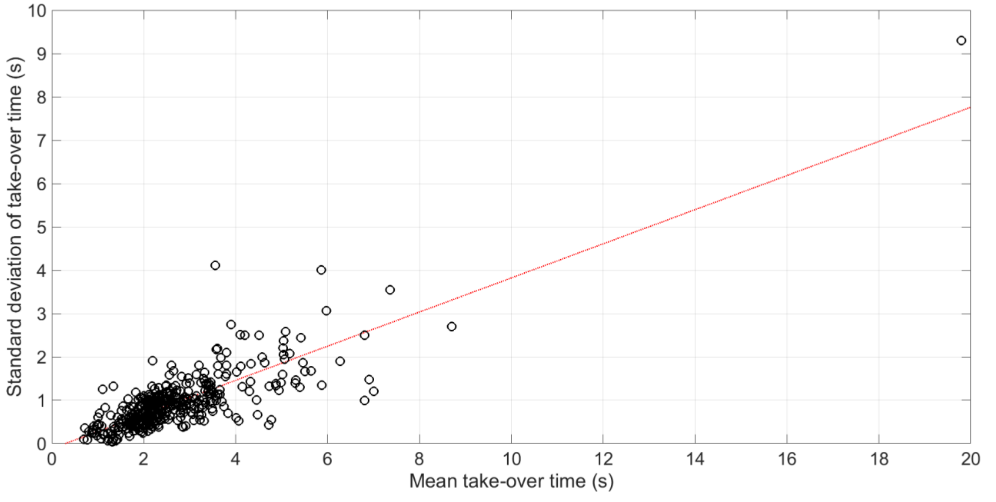

Figure 2.4 Scatter plot of the standard deviation of the take-over time (SD TOT) as a function of the mean take-over time (mean TOT), with a fitted least-squares regression line (n = 397).

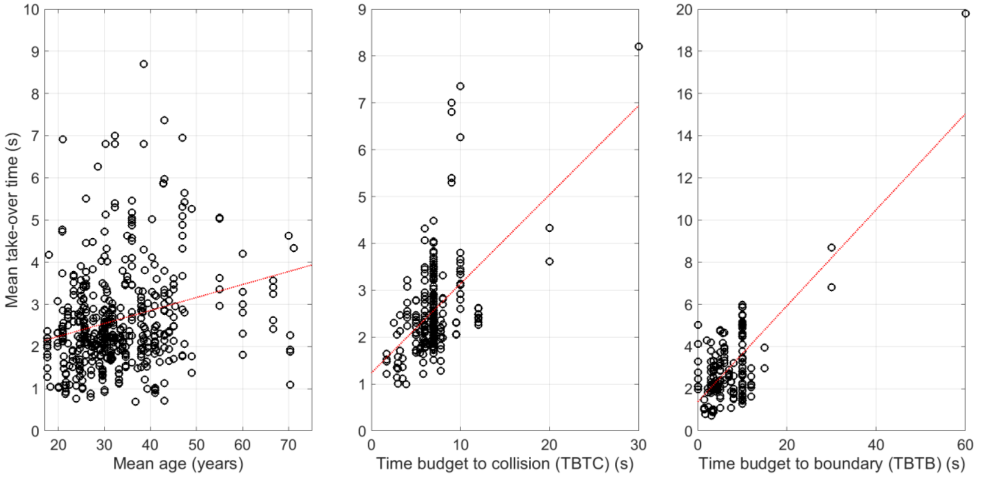

Figure 2.5 Scatter plot of the mean take-over time (mean TOT) as a function of a) mean age of the participant group (n = 485), b) take-over time budget to collision (TBTC, n = 240), c) take-over time budget to other boundaries (TBTB, n = 160), with a fitted least-squares regression line. A TBTB of 0 s means that the automation was deactivated at the moment of the take-over stimulus.

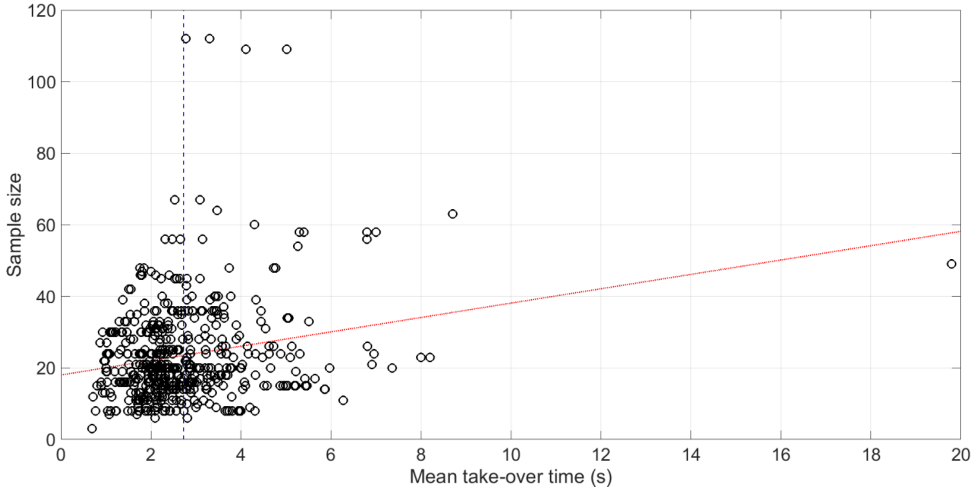

Figure 2.6 Scatter plot of the sample size of the participant group as a function of the corresponding mean take-over time (mean TOT), with a fitted least-squares regression line (n = 520). The vertical line represents the grand mean TOT.

2.3.4 Linear mixed-effects model

The goodness of fit indicators of the linear mixed-effects model are shown in Table 2.4. Table 2.5 shows the estimation results where effects for most study variables were strongly statistically significant (i.e., low p-values). The model predicting "ln(TOT)" (i.e., the logarithm of the mean TOT) is specified according to Eq. (1):

$$ln(\mathrm{TOT}) = \alpha + \beta_{\mathrm{LAD}} \cdot \mathrm{LAD} + \beta_{\mathrm{TOR_A}} \cdot \mathrm{TOR_A} + \beta_{\mathrm{TOR_{VT}}} \cdot \mathrm{TOR_{VT}} + \beta_{\mathrm{NDT_V}} \cdot \mathrm{NDT_V} + \beta_{\mathrm{MissNDT_V}} \cdot \mathrm{MissNDT_V} + \beta_{\mathrm{HAND}} \cdot \mathrm{HAND} + \beta_{\mathrm{MissHAND}} \cdot \mathrm{MissHAND} + \beta_{\mathrm{URG_{High}}} \cdot \mathrm{URG_{High}} + \beta_{\mathrm{URG_{Med}}} \cdot \mathrm{URG_{Med}} + \beta_{\mathrm{MissURG}} \cdot \mathrm{MissURG} + \beta_{\mathrm{IRU}} \cdot \mathrm{IRU} + \beta_{\mathrm{MissIRU}} \cdot \mathrm{MissIRU} + \gamma \cdot \vartheta + \sigma \cdot \varepsilon \qquad (1)$$

where α is the intercept, β_{LAD}, $\beta_{\mathrm{TOR_A}}$, $\beta_{\mathrm{TOR_{VT}}}$, $\beta_{\mathrm{NDT_V}}$, β_{HAND}, $\beta_{\mathrm{URG_{High}}}$, $\beta_{\mathrm{URG_{Med}}}$, β_{IRU} are the parameters associated with the study variables listed in Table 2.5, $\beta_{\mathrm{MissNDT_V}}$, $\beta_{\mathrm{MissHAND}}$, β_{MissURG}, β_{MissIRU} are parameters associated with the dummy variables indicating the missing values, γ is the parameter associated with the study-specific error term $\vartheta \sim \mathrm{N}(0,1)$, and σ is the parameter associated with the observation-specific error term $\varepsilon \sim \mathrm{N}(0,1)$. The study-specific error term captures between-study variance and the observation-specific error term captures residual variance between observations. We selected the study variables based on statistical significance. The other study variables listed in Table 2.1 did not significantly influence the mean TOT.

Studies carried out with high levels of automation (≥ SAE level 3) showed longer mean TOTs than studies with partial automation (SAE Level 2). The fidelity of the driving simulator did not significantly influence mean TOTs (i.e., was not a sufficiently strong predictor to be included in the model as a predictor variable). Auditory and vibrotactile TOTs were associated with shorter mean TOTs, whereas visual warnings did not have a statistically significant impact on mean TOTs. Participants were slower in taking over control when they were engaged in visual non-driving tasks. Other types of non-driving tasks (auditory, motoric, and cognitive) did not significantly influence mean TOTs. Participants showed longer mean TOTs when holding a handheld device. Take-over situations with high and medium levels of urgency were related to shorter TOTs than situations with a low level of urgency. Finally, taking into account one or more other road users was associated with a longer mean TOT as compared to when no road users were driving in the vicinity.

Table 2.4: Characteristics of the linear mixed-effects model

Number of parameters	14
Number of studies	129
Number of observations	520
-2 Restricted log likelihood	132.2
Akaike's Information Criterion (AIC)	136.2
Schwarz's Bayesian Criterion (BIC)	144.6

Table 2.5: Results of the linear mixed-effects model. The parameters represent the unconditional marginal effects of the study variables on the logarithm of the mean TOT.

Variable	Description	Parameter	Estimate	df	t	p
	Intercept	α	1.06	203.39	11.12	**$9.39*10^{-23}$**
LAD	Equal to 1 when the level of automated driving (SAE International, 2016) is L3 or above as reported by the authors of the paper	β_{LAD}	0.285	140.51	3.11	**$2.24*10^{-3}$**
TOR_A	Equal to 1 when the TOR contains an auditory stimulus	β_{TOR_A}	-0.213	451.50	-5.29	**$1.89*10^{-7}$**
TOR_{VT}	Equal to 1 when the TOR contains a vibrotactile stimulus	$\beta_{TOR_{VT}}$	-0.180	450.54	-4.00	**$7.53*10^{-5}$**
NDT_V	Equal to 1 when the NDT is visual	β_{NDT_V}	0.0975	450.68	3.32	**$9.56*10^{-4}$**
$MissNDT_V$	Equal to 1 when it is not mentioned whether the NDT is visual	$\beta_{MissNDT_V}$	-0.155	151.99	-0.62	$5.36*10^{-1}$
HAND	Equal to 1 when a device is handheld when undertaking the NDT	β_{HAND}	0.231	461.09	6.32	**$6.22*10^{-10}$**
MissHAND	Equal to 1 when it is not mentioned whether a device is handheld when undertaking the NDT	$\beta_{MissHAND}$	-0.0559	507.00	-0.63	$5.29*10^{-1}$

$\mathrm{URG_{High}}$	Equal to 1 when there is an immediate risk of collision (time budget ≤ 8 s), or the participants were instructed to react to a stimulus as quickly as possible.	$\beta_{\mathrm{URG_{High}}}$	-0.466	491.88	-8.14	**3.17*10^-15^**
$\mathrm{URG_{Med}}$	Equal to 1 when there is potential collision risk or disturbance to other road users if no response is made, or a medium time budget (between 8 s and 15 s).	$\beta_{\mathrm{URG_{Med}}}$	-0.219	506.95	-3.62	**3.21*10^-4^**
MissURG	Equal to 1 when it is not mentioned whether there is an immediate risk	β_{MissURG}	-0.142	145.68	-0.77	4.44*10^-1^
IRU	Equal to 1 when the participants had to take into account one or more other road users when choosing their optimal take-over action.	β_{IRU}	0.182	502.89	4.57	**6.13*10^-6^**
MissIRU	Equal to 1 when it is not mentioned whether the driver had to take into account one or more other road users when choosing their optimal take-over action.	β_{MissIRU}	-0.0220	336.49	-0.18	8.59*10^-1^
Error term	Description	Parameter	Estimate		Wald-Z	p
ϑ_s	Study-specific error term (between-study variance)	γ	0.136		6.89	**5.40*10^-12^**
ε_s	Observation-specific error term (between-observation variance)	σ	0.0375		13.73	**6.73*10^-43^**

p < 0.05 is indicated in boldface

The model coefficients in Table 2.5 are defined on a logarithmic scale, which enhances the model fit, but complicates the interpretation. To illustrate the impact of the study variables on the mean TOT in seconds, we used the linear mixed-effects model to calculate the mean TOT in a baseline observation and the mean TOT where one variable was changed while keeping all the other variables fixed. In the baseline observation, the level of automation was high (≥ SAE level 3), the TOR was auditory, the NDT was visual, and the level of urgency was high. In addition, drivers did not use a handheld device and did not have to take into account other road users. These baseline values were selected because they represent the majority of the conditions available. The impact of the study variables on the mean TOTs is shown in Table 2.6. The level of urgency, holding a device in the hands, and the use of an auditory TOR had the largest impact on the mean TOTs.

Table 2.6: Effect of the study variables on the baseline TOTs (average baseline TOT = 2.15 s).

Variable	Estimated mean TOT (s)
LAD = 0	1.62
TOR_A = 0	2.66
TOR_VT = 1	1.80
NDT_V = 0	1.95
Hand = 1	2.71
URG_Low = 1	3.43
URG_Med =1	2.75
IRU = 1	2.58

2.4 Discussion

2.4.1 Findings from this Meta-Analysis

This meta-analysis quantified the determinants of mean take-over time (TOT) as observed in 129 experiments using three complementary approaches: a within-study analysis, a between-study analysis, and a linear mixed-effects model. The within-study analysis provides a synthesis of causal experimental effects (Figure 2.3). The between-study analysis is based on correlations that involve hundreds of mean TOT values (Table 2.2), and may, therefore, feature higher generalizability than the within-study analysis. However, the between-study analysis is a synthesis of correlations rather than causal effects, and may therefore be susceptible to various confounding factors. The linear mixed-effects model is statistically powerful because it uses the dataset of the between-study analysis while taking into account whether the mean TOT values were obtained from the same study. Although all models are wrong if taken literally (Box, 1976), we would argue that our three-fold complementary approach provides a good picture of the current take-over literature.

Several main findings stand out from the three meta-analysis methods. First, the urgency of the situation, defined in terms of (1) the hand-coded urgency level (URG), (2) time budget to collision with an obstacle (TBTC), and (3) time budget to boundaries (TBTB), has substantial associations with the mean TOT. In other words, if more time is available, drivers use more time to take over. This observation is consistent with previous reviews (see Section 2.1.2) and can be interpreted using a literature review by Summala (2000) on brake reaction times in manual driving. Summala argued that a distinction exists between drivers’ ability to intervene quickly and their motivation to intervene, and explained that “it is not always necessary to react as soon as possible”. If there is sufficient time, drivers do not take-over as quickly as they can, but first assess the situation (e.g., by checking the mirrors) (Gold, Damböck et al., 2013) and resume an optimal driving posture (e.g., by adjusting the seating position) (Zhang et al., 2019) before taking over.

The second finding is that performing a non-driving task with a handheld device strongly increases the mean TOT, as confirmed by each of the three analyses. Among the studies without a handheld device, performing a visual NDT yielded a moderate increase in mean TOT as compared to not performing such a task. The mixed-effects model confirmed that engagement in a visual NDT increased mean TOTs. The other modalities of the NDT, that is, whether the task demand is auditory or cognitive, did not show significant associations with the mean TOTs. Zhang et al. (2019) examined driver perception and movement response times during take-over process, and found that physically switching arm posture from the current NDT to the driving control task requires more time than perceiving and cognitively processing the take-over stimuli, especially when the arm movement amplitude is high (cf. Fitts, 1954).

Third, a high level of automation (SAE L3 and above) showed higher mean TOTs compared to partial automation (SAE L2), possibly due to a combined effect of a longer time budget, lower urgency, and more involvement in (handheld) NDTs, consistent with the definition provided by the SAE International (2016).

Fourth, as shown in the within-study analysis, prior experience with taking over has a strong effect: drivers responded about 1 second faster if the take-over scenario occurred the second time compared to the first time. The majority of the included studies (92 out of 129) used a within-subject design. In a review about brake response times in manual driving, Green (2000) pointed out that in most studies, participants performed multiple trials to generate more data. The repeated trials would contribute to shorter response times, which calls for caution when interpreting the results. Our meta-analysis also showed that drivers responded about 0.5 seconds faster when the TOR could be anticipated from task-related or environmental cues. This finding is in line with publications indicating that expectancy is an important factor influencing brake response times (Green 2000; Warshawsky-Livne & Shinar, 2002; Young & Stanton, 2007).

Fifth, visual-only TORs showed longer mean TOTs than auditory or vibrotactile TORs. The mixed-effects model further showed that auditory and vibrotactile TORs reduce the mean TOTs as compared to when such TORs are not present or the TOR is visual only. Petermeijer, Doubek, and De Winter (2017) argued that a visual-only warning is not suitable as a TOR, as drivers may overlook a visual signal (especially if they are performing a visually distracting NDT) or may not interpret a visual signal as urgent. Auditory warnings, on the other hand, are well established due to their omnidirectional characteristics (Bazilinskyy & De Winter, 2015). Vibrotactile TORs are effective as well, as they can attract the driver's attention when the driver is performing a visual or auditory NDT (Petermeijer et al., 2016).

Sixth, we found no clear effect of age in the within-study analysis or the multi-level model, which is interesting because age is known to be associated with a slower speed of processing (e.g., Salthouse, 2009). One possible explanation is that TOTs largely reflect motivational processes, not biological limitations, as pointed out above. For example, although older drivers have a slower simple reaction time, they could have a more cautious driving style and are likely to take over quickly even when not strictly necessary (Körber, Gold, Lechner, & Bengler, 2016). Compensatory behaviours, such as a less intensive involvement in NDTs, may also alleviate ageing effects (Clark & Feng, 2017). Furthermore, the positive correlation between age and mean TOT in the between-study analysis may point to a confounding effect, where older drivers have participated in different types of experiments, as discussed below. We argue that the lack of observed age effects in the within-study analysis is not due to range restrictions, as the differences in mean age for the six included studies were substantial (23 vs. 67 years, 20 vs. 70 years, 34 vs. 60 years, 18 vs 70 years, 18 vs. 37 years, 26 vs. 71 years). It has been recommended that future take-over studies include even older drivers, above 80 years of age (e.g., Körber et al., 2016, Li, Blythe, Guo, & Namdeo, 2018). Additionally, we would recommend that future research on the effect of biological age on TOT should try to obtain a more in-depth understanding by examining the effects of covariates, such as years of driving experience, psychometric performance (e.g., simple, reaction time, perceptual speed), and sensation seeking scores.

Finally, we found a moderate effect of surrounding traffic (IRU) on the mean TOT. This can be explained by the fact that drivers, in case of surrounding traffic, need time for visual scanning and situation assessment before taking over. However, we found that a more complex driver response (i.e., higher DRE) was associated with a shorter mean TOT in the between-study analysis. This counterintuitive finding could be due to the strong positive correlation between DRE and urgency. In other words, although complex responses require cognitive processing time (see e.g., Gold, Naujoks et al., 2018, and Green, 2000 for discussion in manual driving context), such responses are more likely to be performed in urgent situations, which are associated with lower mean TOTs.

2.4.2 Limitations

The current study was performed using mean TOTs. In the end, collision risk is not determined by the mean TOT, but by outliers in the TOT distribution (Horrey & Wickens, 2007). We found that the mean and standard deviation of TOT are highly correlated ($r = .82$; $\rho = .73$), indicating that mean TOTs are informative about the tail of the TOT distribution. However, we note that accidents may be due to extreme values (e.g., TOTs that exceed the 99.999th percentile, such as due to a driver being asleep behind the wheel). Our meta-analysis is not suitable for making inferences about crash likelihood or for proposing generic guidelines about what time budget constitutes safety.

A second limitation is that this meta-analysis investigated take-over *time*, not take-over *quality*. A number of studies found fast but also hazardous responses (severe braking or steering) under higher mental workload and short time budgets (e.g., Gold, Damböck et al., 2013; Clark & Feng, 2017; Ito, Takata, & Oosawa, 2016). Put differently, a short TOT does not necessarily indicate a safe situation, but could actually be a sign of hazard, because short TOTs typically occur in urgent situations for which an evasive manoeuvre may be needed. We found that directional TORs (i.e., TORs that are informative about the location of the hazard) have no beneficial effects on mean TOT, but this does not imply that directional TORs are ineffective, as they could be useful to enhance take-over quality (e.g., to enhance situation awareness). We recommend that researchers publish not only the mean and standard deviation of the TOT, but also provide data files with TOT values per event. This would allow meta-analysts to make inferences about the TOT distribution. Additional response variables, such as minimum time to collision and maximum longitudinal/lateral acceleration would enable the assessment of take-over quality.

Third, the starting moment of the take-over response is a source of ambiguity (Liu & Green, 2017). While some researchers used criteria such as “the moment the driver gave an input either on the pedals or the steering wheel” (Payre, Cestac, Dang, Vienne, & Delhomme, 2017), other researchers provided exact criteria. For example, Gold, Damböck et al. (2013) adopted a 2 degree steering angle or 10% brake pedal position, which was employed in a number of subsequent studies (Feldhütter, Gold, Schneider, & Bengler, 2017; Gold et al., 2015; Gold, Körber, Lechner, & Bengler, 2016; Gold et al., 2014; Gold, Lorenz, Damböck, & Bengler, 2013; Kerschbaum et al., 2015; Körber et al., 2016; Radlmayr et al., 2014). Somewhat different criteria can be found in other studies, such as absolute steering acceleration larger than 5 deg/s^2 (Zeeb, Buchner, & Schrauf, 2015, 2016). Another issue is that the TBTC posed an upper limit to the TOTs that could be observed; if a participant would not react at all (which sometimes happened, see Gold, Lorenz et al., 2013; Young and Stanton, 2007), their results were not taken into account in the reported mean TOT, which would underestimate the mean TOT.

Fourth, although a large number of study variables were investigated, there may still be unobserved study variables that affect TOT. Examples of hidden moderators are driving speed, the intensity of the TOR, and the state of the operator (e.g., whether he or she is fatigued or impaired by alcohol, see Wiedemann et al., 2018). Hidden moderators may also explain why the study-specific error term is strong in the mixed-effects model.

Fifth, nearly all included studies were conducted in a driving simulator. Despite advantages such as controllability and safety, driving simulators have limited fidelity, which raises the issue about behavioural validity (De Winter, Van Leeuwen, & Happee, 2012; Green, 2000; Kaptein, Theeuwes, & Van der Horst, 1996; Riener, 2010; Risto & Martens, 2014). Also, the driver's level of perceived risk perception may be low in simulators as compared to on-road conditions (Carsten & Jamson, 2011), which could discourage a fast take-over response. While the TOTs measured in simulator studies may not accurately reflect the numeric values of the TOTs in the real world, the results may still be valid concerning the direction of the effects (Kaptein et al., 1996).

Sixth, although our meta-analysis is much more comprehensive compared to previous reviews on the same topic (see Introduction), the within-study analysis would still benefit from a larger sample of studies. The Ds in Figure 2.3 are based on 4 to 17 studies. Although each of these individual studies may present credible findings, more studies should be conducted to examine whether the experimental effects are generalizable.

Finally, as in any meta-analysis, there may be sources of bias or confounding effects. In a previous review on automated driving, De Winter et al. (2014) observed a confounder, namely that young participants are overrepresented in lower-fidelity driving simulators. The authors explained that lower-fidelity simulators are available at universities where participants are usually students, whereas companies with high-fidelity simulators tend to recruit middle-age drivers. A similar association between simulator fidelity level and participant age was observed in the between-study meta-analysis (ρ = 0.38). We also found studies in lower-fidelity simulators involved larger sample sizes (ρ = -0.25), which could be explained because students participate in relatively large amounts, e.g., for course credit. Such confounds affect some of the correlations in the between-study analysis (Table 2.2), but are controlled for in the mixed-effects model. In the between-study analysis, a weak-to-moderate correlation was observed between sample size and mean TOT, which may be related to the confounding effect of simulator fidelity discussed above.

We expect that publication bias regarding mean TOT in the between-study analysis is small as compared to other types of research such as drug trials where researchers and sponsors may favour a positive drug efficacy. That is, we are not aware of a mechanism by which the mean TOT would affect the likelihood of publication. The scatter plot of sample size vs. mean TOT (Figure 2.6) showed no characteristic funnel shape, likely because the observed spread in mean TOT reflects study heterogeneity rather than imprecision of the mean TOT values.

Regarding the within-study analysis, where we assessed differences in mean TOT (D), publication bias is possible but not evident from our findings. For example, innovative types of TORs where publication bias may be expected (e.g., directional and peripheral TORs) showed near-zero effects (Figure 2.3), thus indicating that small (null) effects were published. The number of studies per category of the within-subject analysis was too small to create funnel plots or perform a formal test of publication bias.

2.4.3 Conclusion and Recommendations for Future Research

The meta-analysis included 129 studies that measured driver TOTs when resuming manual control after automated driving and investigated the effect of multiple factors related to the driver, the automation system, the human-machine interface, the driving situation, and the experimental setup. Notable findings are that the available time, a lack of experience with TORs, and using a handheld device were associated with substantially increased mean TOT. Although providing a take-over request yields a lower mean TOT than no take-over request at all (or a visual-only take-over request), the modality of the TORs had relatively minor effects on the mean TOT.

These findings have important implications for future research and design. In particular, instead of designing new types of take-over requests that may have only incremental effects on mean TOT, efforts could be made towards ensuring that drivers are prepared and trained to take over. Also, drivers should not be permitted to engage in handheld non-driving tasks if take-over situations can be urgent. Conducting non-driving tasks on a mounted (head-up) display could be a safer option in such cases.

Finally, our meta-analysis suggests that achieving a low mean TOT should not necessarily be a design target. We showed that drivers take more time (i.e., the mean TOT is higher) when they have more time (i.e., when the urgency is lower). Future engineering efforts should be directed towards ensuring that drivers actually have sufficient time, which could be done by building better sensors with larger look-ahead time or by using vehicle-to-vehicle communication.

2.5 Supplementary material

Supplementary materials are accessible via this link: https://doi.org/10.4121/uuid:75c28abe-6559-4273-85f4-927e969c1c59

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3. Transitions to manual control from highly automated driving in non-critical truck platooning scenarios (with hand-held NDT)

This chapter is based on: Zhang, B., Wilschut, E. S., Willemsen, D. M. C., & Martens, M. H. (2019). Transitions to manual control from highly automated driving in non-critical truck platooning scenarios. Transportation Research Part F: Traffic Psychology and Behaviour, 64, 84-97. (adapted with minor textual changes)

3.1 Introduction

Over the past decade, the rapid advancement of intelligent transport systems (ITS) and sensor technology has been dramatically changing the automotive industry. The first (semi-)automated systems already available are designed for specific driving situations. For example, some cars already have systems such as traffic jam assist that work at low speeds, or automated driving on highways. These systems are primarily based on Adaptive Cruise Control (ACC), which allows a vehicle to maintain a predefined headway to the vehicle in front, combined with Lane Keeping Assist Systems (LKAS) that take control of the lateral position of a car within its lane primarily on the basis of road markings. In a recently published naturalistic driving study, Endsley (2017) reported her experience with the Tesla Model S over a period of six months, during which considerable number of trips were performed in autopilot mode. Besides automated passenger cars, automated truck platooning, defined as a team of virtually connected trucks traveling together at short following distances, is also getting increasing attention for its potential positive effects on energy saving, driver workload, traffic flow, and safety (Alam, Besselink, Turri, Martensson, & Johansson, 2015; Bergenhem, Shladover, Coelingh, Englund, & Tsugawa, 2012; Hjälmdahl, Krupenia, & Thorslund, 2017; Willemsen, Stuiver, & Hogema, 2015). The lead truck is normally driven by a human driver, and the trucks behind follow the lead truck with automated longitudinal control (e.g., via Cooperative Adaptive Cruise Control (CACC), as described in Ploeg, Van de Wouw, & Nijmeijer, 2014) or with both automated longitudinal and lateral control (e.g., combining CACC and LKAS). Although truck platooning has not yet been implemented as a commercial product, various demonstrations and pilots already showed its potential. One example is the European Truck Platooning Challenge (2016), in which six European truck manufacturers brought platoons of trucks equipped with various automation technologies on public roads, travelling from various European cities to the final destination of the Port of Rotterdam.

In these real-life applications and truck platooning demonstrations, drivers are still required to attentively monitor the driving environment and be prepared to take over instant manual control upon the detection of operational limits of the system (i.e., Level 2 automation as defined by SAE International, 2016). Studies with passenger cars have shown that this level of automation may not require less attentional demand compared to manual driving (Stapel, Mullakkal-Babu, & Happee, 2019; Stapel, Mullakkal-Babu, & Happee, 2017). Unscheduled and critical transitions of control can be particularly dangerous for drivers in the platoon, because the available time budget is usually very small due to the short following distance used for platooning. In the foreseeable future, the working range and the reliability of these systems will continue to develop towards a situation in which the driver is allowed to be temporarily out of the loop (Merat et al., 2018) and relax (SAE level 3 or level 4 automation). In certain situations, such as approaching the exit of a motorway and thus dissolving the platoon, transitions of control to human drivers may still occur. These transitions will have to be sophisticatedly designed to ensure that drivers will be ready to take over control safely and comfortably. This can be challenging, because increasing levels of automation may have negative impact on drivers' ability to take over control due to factors such as increasing engagements in non-driving tasks (Jamson, Merat, Carsten, & Lai, 2013), loss of situation awareness (Endsley, 1995), boredom, and fatigue (Körber, Schneider, & Zimmermann, 2015). Also, the variability in driver activities and mental states during automated driving can subsequently cause large differences in driver response towards similar stimuli. A good understanding of driver takeover behaviour and performance under various task conditions becomes essential for the development of future intelligent vehicles.

Typically, taking over control includes several mental and physical processing procedures: perception of the take-over stimulus (normally a take-over request (TOR) issued by the system), cognitive processing of the traffic situation, response selection, resuming motor readiness (by repositioning the hands on the steering wheel and feet on the pedals), and implementation of an intervention (Gold & Bengler, 2014; Petermeijer, De Winter, & Bengler, 2016; Zeeb, Buchner, & Schrauf, 2015, 2016). Multiple factors have been suggested to influence the response time (RT) to complete the take-over process (i.e., take-over time) and other take-over performance parameters, such as human-machine interface (HMI) design (Carsten & Martens, 2019; Melcher, Rauh, Diederichs, Widlroither, & Bauer, 2015; Van den Beukel, Van der Voort, & Eger, 2016; Willemsen, Stuiver, Hogema, Kroon, & Sukumar, 2014), driver inattention and engagement in non-driving tasks (Louw, Kountouriotis, Carsten, & Merat, 2015; Petermann-Stock, Hackenberg, Muhr, & Mergl, 2013; Radlmayr, Gold, Lorenz, Farid, & Bengler, 2014; Wandtner, Schömig, & Schmidt, 2018; Zeeb, Härtel, Buchner, & Schrauf, 2017), urgency of the take-over situation (Gold, Damböck, Lorenz, & Bengler, 2013; Ito, Takata, & Oosawa, 2016; Roche & Brandenburg, 2018), and traffic complexity (Gold, Körber, Lechner, & Bengler, 2016; Jamson et al., 2013; Radlmayr et al., 2014). Zhang, De Winter, Varotto, Happee, and Martens (2019) conducted a meta-analysis on take-over times from 129 studies with SAE level 2 automation or higher, showing that the mean values ranged largely between 0.7 s and 20 s across various experimental studies and conditions. The reviewed studies were predominantly car automation studies. Eriksson and Stanton (2017) pointed out that most of the previous efforts focused on driver take-over time in critical situations, given a predetermined take-over lead time (i.e., the maximum time allowed for a driver to response to a critical event). Greater perceived urgency can shorten take-over times, but on the other hand can also force the driver to take over before being well prepared (Gold et al., 2013; Lu, Happee, Cabrall, Kyriakidis, & De Winter, 2016). Therefore, take-over times measured under critical situations cannot reflect the time drivers ideally need to get prepared, and achieving a short take-over time is not always necessary or beneficial (Zhang et al., 2019). Advanced strategies such as multi-step control transitions and adaptive control transitions (e.g., taking driver states into consideration) may help the driver to gradually get back into the loop, and take over more safely and comfortably. To be able to develop such strategies, and to design scheduled (and therefore non-critical) transitions, it's necessary to understand how long it takes for a driver to conduct the self-regulated control transition process. Eriksson and Stanton (2017) exclusively looked into non-critical take-over scenarios without time restrictions in a passenger car mock-up simulator, and reported largely varied take-over times ranging from 1.9 s to 25.7 s. We have not been able to identify studies that have used professional truck drivers as participants in a truck mock-up driving simulator, with the focus on take-over response times and performance when leaving a platoon in non-critical scenarios.

Due to the fact that driver take-over is a complex procedure, it is of interest to understand how long it takes to complete various information processing stages and come to action, and how these take-over time components are influenced by various factors. In previous studies, researchers often reported RTs measured from the TOR onset until the first contact with the steering wheel/pedal to indicate the motor or physical readiness of the driver, and the start of the intervention (by braking, steering, or button pressing) to indicate the initiation of a conscious response to the take-over scenario (e.g., Zeeb et al., 2015, 2016, 2017). If the driver was visually distracted before the TOR onset, some researchers also measured the RTs when the driver first shifted the gaze away from the visual non-driving task, and when the first fixation on the road occurred (e.g., Gold et al., 2013; Körber, Gold, Lechner, & Bengler, 2016; Feldhütter, Gold, Schneider, & Bengler, 2017). This was done to investigate when the driver shifted the visual attention to the road and started to process the information gathered from the driving environment. In a few studies, additional actions were registered, such as the first mirror check and the first operation of a turn signal (e.g., Gold et al., 2013; Petermeijer, Doubek, & De Winter, 2017).

In studies on manual driving, the concept of perception-response time is frequently utilized to investigate drivers' brake responses (see the review of Green, 2000), which comprises two components: the perception RT and the movement RT. The perception RT can be defined as the time it takes for the driver to perceive a stimulus, cognitively process the situation, and decide on a response. The movement RT is the time required to perform the actual programmed motoric action. For the analysis of driver take-over times, if only considering the basic response to the TOR, the division between the perception RT and the movement RT would be the start of the hand/foot movement towards the steering wheel/pedal. Moving hands or feet indicates that the driver has perceived and recognized the meaning of the TOR (i.e., they need to take over control), and has decided to regain motor readiness, which marks the end of the perception RT and the start of the movement RT. These two RT components are suggested to have different explanatory variables. For instance, the perception RT can be more related with the characteristics of the take-over stimulus (e.g., modality and intensity of the TOR) and driver monitoring strategies (e.g., how long and how frequently did the driver look onto/off the road, see Zeeb et al., 2015, 2016), while the movement RT can be more related to the complexity and the amplitude of the motoric manoeuvre (cf. Fitts, 1954), such as putting away a hand-held device. Note that the movements of hands and feet do not have to be the result of a decision about the required action after the comprehension of the current situation, especially in critical scenarios where the movements could be an automated response (i.e. as a reflex). To regain situation awareness may require a considerable amount of time (Lu, Coster, & De Winter, 2017), the process of which could overlap with, or even exceed the movements to resume manual control.

In the manual driving context, the movement RT is often neglected since it only refers to the foot traveling time from the acceleration pedal to the brake pedal, which normally takes less than 0.5 s (Green, 2000). When studying driver behaviour in highly automated driving, taking over control is more of a task-switching process (i.e., to perform two tasks in succession, see Monsell, 2003) rather than multi-tasking such as being distracted during manual driving (Louw, Merat, & Jamson, 2015; Young & Stanton, 2007; Zeeb et al., 2017). This change of paradigms leads to an expansion of non-driving task classifications from simply listening to the radio to complex tasks incompatible with driving, such as writing emails, playing computer games, or even resting with eyes closed (see Naujoks, Befelein, Wiedemann, & Neukum, 2017 for a review). When engaged in non-driving tasks, drivers' postures become less predictable and may heavily influence take-over times. Therefore, the distinction between the perception RT and the movement RT has its added value for a deeper insight into factors influencing driver take-over times and the individual differences. However, very few researchers reported the start of the hand movement when studying take-over times (Kerschbaum, Omozik, Wagner, Levin, Hermsdörfer, & Bengler, 2017; Kerschbaum, Lorenz, & Bengler, 2015). The perception-response time during driver take-over process is little addressed up to now.

In summary, a closer examination of drivers' take-over process and the variability in non-critical take-over situations, particularly in case of truck platooning, is needed to design safe and comfortable transitions of control. The current study aims to investigate how various task conditions influence truck drivers' perception-response times when receiving a request to leave the platoon and take back control, and to explore the factors influencing the variability in this process based on video observations. The factors explaining the RT components and their variability can be used towards the design of an adaptive transition approach.

3.2 Methods

3.2.1 Participants

Twenty-two participants (2 females) took part in the experiment. They all held a truck driver's license for at least eight years (M = 28 years, SD = 12) and drove at least 10.000 km per year in a truck (M = 35219 km/year, SD = 27508). On average, the participants were 47.4 years old (SD = 11.5), ranging from 27 to 64 years old. The research was approved by the Ethical Committee for participant studies of TNO.

3.2.2 Apparatus

The experiment was conducted at TNO in a high fidelity moving base driving simulator consisting of a DAF truck mock-up (see Figure 3.1). The road and traffic environment were projected on cylindrical screens around the vehicle with an 180 degree field of view. Two screens placed behind the vehicle showed the scenery for the rear view mirrors. Vehicle related data including the input of the control elements and the status change of the automation system were recorded by the simulator at a sampling rate of 50 Hz. In addition, the participants' head motion and eye movements were recorded by a non-obtrusive remote eye tracker (SmartEye AB, Gothenburg, Sweden). The mock-up was also equipped with three cameras to observe the drivers' full body postures, facial expressions, and feet positions, respectively.

Figure 3.1: TNO truck driving simulator with moving hexapod and cylindrical projection screen

3.2.3 Two-truck platoon system

An automated system was simulated that allows a truck to follow a lead truck at a short following distance on public motorways, initially limited to platoons of two trucks. The first truck is intended to be driven by a human truck driver (but is controlled by the simulator in this experiment). Once engaged, the second truck is controlled by the automation system (Figure 3.2). The participant in the driving simulator was the driver of the second truck in the platoon. For the participant, the center view of his/her own lane was blocked by the lead truck, but the view of the adjacent lanes was unblocked, as shown in Figure 3.3.

The automated system was modelled as a combination of CACC and LKAS. The driver could push a button normally used for cruise control on the right side of the steering wheel to switch the automation system on/off. To be able to switch the system on, the driver had to drive in an activation zone behind the lead truck. After activating the system, the vehicle controlled both longitudinal and lateral control and did not have to be monitored, thus simulating SAE L4 automated driving. At the end of the automated driving period, the system would indicate that the driver had to take over control by displaying a text message on the screen (Figure 3.4, in Dutch: ‘‘Neem de controle over”, in English: ‘‘Take over control”), accompanied by an auditory signal. The driver had to push the button again to resume both longitudinal and lateral manual control and leave the platoon.

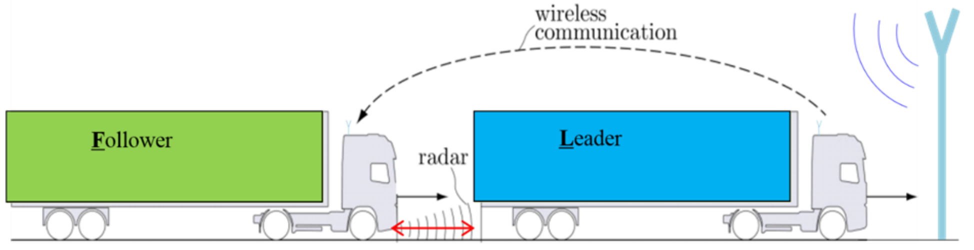


Figure 3.2: Two-truck platoon system

Figure 3.3: Front view in the second truck. The center of the ego lane was blocked by the lead truck, while the driver was able to perceive traffic information from the adjacent lanes

Figure 3.4: Visual interface of the take-over request (text in Dutch: "Take over control")

3.2.4 Experimental design and test procedures

The participants were instructed to drive on the right-hand lane of a two-lane motorway behind a lead truck at an average speed of 80 km/h. The route included slight curves and moderate surrounding traffic, but no entries or exits. All participants started with a training session to get familiar with the driving simulator and with platooning. They were asked to perform the coupling and decoupling procedures at least three times, until they felt familiar and comfortable with the system.

After the training, each participant performed eight platooning trials in different test conditions, in which four variables were manipulated: non-driving tasks (no task, using a handheld tablet PC, and relaxing with eyes closed), criticality of the control transition (self-regulated non-critical transition vs. critical transition due to unexpected system failure), time gaps between the trucks (0.8 s vs. 0.3 s), and whether a brake event was implemented after the control transition back to the driver. The system failure trial was always performed at the end of the experiment, while the other trials were conducted in a counterbalanced order. This paper only discusses the five non-critical trials in which the time gap was set to 0.8 s during automated driving. This distance is the minimum allowed time gap defined in ISO 15622, and is considered as an accepted distance for testing the first platooning concepts with truck drivers. The other trials will not be further described (please see Wilschut, Willemsen, Hogema, & Martens, 2016 for more details on this project, and Zhang, Wilschut, Willemsen, Alkim, & Martens, 2017 for the critical transition trial).

In three trials, no events were programmed after the control transition back to the driver. They serve as the basis of the study to investigate drivers' performance when leaving the platoon and stabilizing the truck in normal, uneventful transitions. In each trial, participants started with a short period of manual driving, then activated the platooning system to follow the lead truck automatically. During the automated driving segment, each participant was subjected to one of the three task conditions as briefly mentioned above: Driver Monitoring (participants were instructed to monitor the surroundings constantly, so hands-off, feet-off, and eyes on the road), Driver Not-monitoring (participants were provided with a tablet PC and were asked to use this, so hands-off, feet-off, and eyes off the road, but they were allowed to scan the outside world if they wanted to) and Eyes-closed (participants were not allowed to open their eyes, so hands-off, feet-off, and eyes off the road). These conditions manipulated participants' attentiveness and represented three activities likely to be performed by the driver in future automated vehicles. In particular, the Eyes-closed condition emulated the situation that drivers take a rest with their eyes closed and cannot perceive any visual information, which is very likely to occur at higher levels of automation. After four minutes in the Driver Monitoring condition, or eight minutes in the Driver Not-monitoring and Eyes-closed conditions, the TOR was issued and participants were asked to take over control by pressing the button whenever they felt ready to do so without time restrictions. The automation duration was shorter for the Monitoring condition to increase the possibility that drivers were still paying attention and were alert, and longer for the other two conditions increase the chance of the driver being out-of-the loop. After taking over control, participants continued with a short manual driving phase until the end of the scenario.

To explore whether participants possessed sufficient readiness and situation awareness to cope with more complex situations after the self-regulated transition of control, two additional trials (in Driver Monitoring and Driving Not-monitoring conditions, respectively) with a brake event were implemented. Three seconds after participants took over control, the lead truck started to brake at a deceleration rate of 5 m/s2 for two seconds. No forward collision warnings or brake assist systems were available, and participants had to brake to avoid accidents. The experimental scenario before the brake event was identical to the uneventful trials described above.

3.2.5 Dependent variables

For the basic trials without brake events, three take-over RT components were measured and evaluated, namely the total RT (TRT), the perception RT (PRT), and the movement RT (MRT). The TRT was defined as the time interval from the TOR onset until the moment when participants pressed the button to reclaim control. This value could be directly obtained from the driving simulator data. The PRT was measured from the onset of the TOR until the start of participants' hand movement reaching for the steering wheel, indicating the time elapsed for the participant to perceive and understand the message that they need to take over control, and to decide to resume motor readiness. Subtracting the PRT from the TRT, the MRT was retrieved, showing how long it took the participant to get physically ready. Because this study was about non-critical conditions without time restraints, we assumed that the information perception and processing cycle (in terms of perceiving and understanding the TOR) was finished before participants started to move their hands. The timestamps for the start of the hand movement were manually annotated from the video recordings by two independent observers. A high degree of reliability between the observers was found (the average intraclass correlation coefficient (ICC) was 0.912 with a 95% confidence interval from 0.880 to 0.936). Participants' behaviours during the take-over process were also recorded by the observers to explore the individual differences.

To assess take-over performance (i.e., quality) in stabilizing the truck in its lane, standard deviation of lateral position (SDLP), the number of steering wheel reversals (with a gap of 3 degrees, according to the definition described in SAE International (2015)), the longitudinal speed as well as its standard deviation were analysed. Smaller deviations in lateral position and longitudinal speed, as well as fewer strenuous steering wheel reversals indicate more consistent and seamless control. Previous research showed that to stabilize the vehicle after taking over manual control required around 35–40 s (Merat, Jamson, Lai, Daly, & Carsten, 2014). In the current study, we observed the performance metrics for the first 40 s after the transition. The observation was divided into four timeslots of 10 s except for the steering wheel reversals, which did not occur frequently within such short timeslots. This measure was reported for the entire observation period of 40 s. Additionally, we measured the time gap after taking over control, aiming to understand how drivers regulated the following distance when leaving the platoon.

For the additional trials with brake events, participants' responses to the braking lead truck were evaluated using the brake RT, the minimum time-to-collision (TTC) with the lead truck, and the minimum time headway (THW) to the lead truck. The brake RT was defined as the time interval between the onset of the braking light of the lead truck and the moment when the participant started pressing the brake pedal. The minimum TTC and the minimum THW were calculated for the 10 s after the onset of the braking light of the lead truck. A shorter brake RT, a longer minimum TTC, and a higher minimum THW suggest a safer collision avoidance behaviour and a better performance.

3.3 Results

Due to technical problems, the simulator data in 10 trials (for driving performance assessment), and the video recordings in 13 trials (for perception-response time assessment) were not available for analysis. An overview of data availability per condition is presented in Table 3.1. To make use of all available data on each subject instead of dropping the entire case due to incomplete data, before performing the statistical tests, the missing data were imputed using the expectation maximization (EM) method (Dempster, Laird, & Rubin, 1977) using the 'Missing Data Analysis' command in SPSS 24. The EM method is an iterative procedure that estimates missing data based on available observations using expectation and maximization algorithms, which is suggested to produce more reliable and less biased estimates as compared to traditional missing data handling methods (e.g., mean imputation and regression imputation, see Musil, Warner, Yobas, & Jones, 2002). Results from a preliminary Little's Missing Completely at Random (MCAR) test suggested that the data were missing at random. That is, there appears no systematic or non-random pattern of data omission, and the EM method is considered appropriate. Note that the imputed data were only used for the purpose of statistical tests. All descriptive results were reported based on the raw data without imputation. All statistical analyses were conducted using SPSS 24. The significance level was set to 0.05.

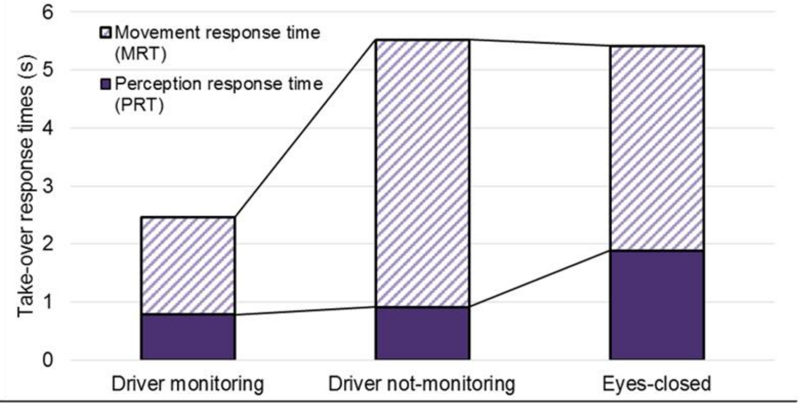
Table 3.1: Overview of data availability

Condition	Total trials performed by the participants	Available datasets for perception-response time	Available datasets for driving performance
Driver Monitoring (w/o BE)	22	18	19
Driver Not-monitoring (w/o BE)	22	17	19
Eyes-closed (w/o BE)	22	18	20
Driver Monitoring (with BE)	22	-	21
Driver Not-monitoring (with BE)	22	-	21

Note. BE = Brake event. The perception-response time was only reported for trials without brake events.

3.3.1 Take-over response times

Averaged over all conditions, the participants took 4.45 s (SD = 2.21) to take over control. The TRT varied from 1.75 s to 11.31 s, and in 95% of the trials participants took over within 8.5 s. The stacked bar plot (Figure 3.5) and the descriptive data table below show an overview of PRTs and MRTs per condition. These two components add up to the TRTs.



	Mean (SD)	Median	Min.	Max.	IQR
PRT					
Driver Monitoring	0.78 (0.14)	0.80	0.43	1.10	0.10
Driver Not-monitoring	0.91 (0.35)	0.87	0.17	1.77	0.33
Eyes-closed	1.89 (1.66)	1.43	0.80	7.73	0.64
MRT					
Driver Monitoring	1.67 (0.49)	1.58	0.95	2.97	0.60
Driver Not-monitoring	4.61 (1.40)	4.07	2.75	7.74	2.01
Eyes-closed	3.53 (1.90)	3.48	1.19	8.31	2.85
TRT					
Driver Monitoring	2.45 (0.53)	2.37	1.75	3.80	0.69
Driver Not-monitoring	5.53 (1.39)	5.36	3.62	8.54	1.86
Eyes-closed	5.42 (2.44)	5.43	2.19	11.31	3.43

Figure 3.5: RT components compared across the three conditions, all measured in second. The bars show the means of MRTs and PRTs per condition; they add up to the TRTs. IQR = Interquartile range.

Because the TRT is not independent from the PRT and the MRT, two separate repeated-measures Analyses of Variance (ANOVA) were performed to examine the effects of task conditions on the total take-over time and its sub-components. A one-way repeated-measures ANOVA was first conducted to analyse TRT. Due to the violation of the assumption of sphericity ($\chi^2(2) = 11.81$, $p = .003$), degrees of freedom were corrected using Greenhouse-Geisser estimates of sphericity ($\varepsilon = 0.69$). There was a significant main effect of task conditions on TRTs ($F(1.38, 29.04) = 43.13$; $p < .001$, $\eta^2 = 0.67$). The post hoc tests showed a significantly shorter TRT in Driver Monitoring condition, in which participants deactivated the automation system on average 3 s earlier than in the other two conditions. No significant differences in TRTs were found between Driver Not-monitoring and Eyes-closed conditions.

Regarding the sub-components of TRTs, a 3 (task conditions) × 2 (RT components) repeated-measures ANOVA was conducted. Mauchly's test indicated that the assumption of sphericity was violated for task conditions ($\chi^2(2) = 11.81$, $p = .003$), and the interaction between task conditions and RT components ($\chi^2(2) = 11.04$, $p = .004$). Degrees of freedom were corrected using Greenhouse-Geisser estimates of sphericity (ε = 0.69 and 0.72). Results showed significant main effects for both task conditions ($F(1.38, 29.04) = 43.13$; $p < .001$, $\eta^2 = 0.67$) and RT components ($F(1, 21) = 85.34$; $p < .001$, $\eta^2 = 0.80$). The interaction between task conditions and RT components was also statistically significant ($F(1.40, 29.49) = 17.96$; $p < .001$, $\eta^2 = 0.46$).

Post hoc pairwise comparisons showed the longest PRT in Eyes-closed condition (M = 1.89 s, SD = 1.66), while no significant differences were found between Driver Monitoring and Driver Not-monitoring conditions. Significant differences in MRTs were found between all condition pairs. The longest MRT was found in the Not-monitoring condition in which the drivers were holding the tablet before the transition (M = 4.61 s, SD = 1.40), followed by the Eyes-closed condition (M = 3.53 s, SD = 1.90). The participants in the Driver Monitoring condition showed the shortest MRT (M = 1.67 s, SD = 0.49). The results further showed that MRTs were significantly higher than PRTs in both Driver Monitoring and Driver Not-monitoring conditions. Although a similar trend was found for the Eyes-closed condition, the difference between the PRT and the MRT didn’t reach statistical significance.

3.3.2 Take-over performance in uneventful trials

With respect to lateral control of manual driving (SDLP) (Figure 3.6), a 3 (Task condition) × 4 (Timeslots: 0–10 s, 10–20 s, 20–30 s, 30–40 s) repeated-measures ANOVA showed significant effects of task conditions ($F(2, 42) = 4.01$; $p = .026$, $\eta^2 = 0.16$) and time ($F(3, 63) = 11.29$; $p < .001$, $\eta^2 = 0.35$). Pairwise comparisons showed a significantly smaller SDLP in the Driver Monitoring condition, but only for the first 20 s. Concerning the function of time, a significantly larger SDLP was found for the first 10 s in all conditions. SDLP became stable and didn’t show significant changes in the following timeslots. Another repeated-measures ANOVA was performed on the number of steering wheel reversals for the first 40 s after taking over control (Figure 3.7). No significant differences were found between task conditions.

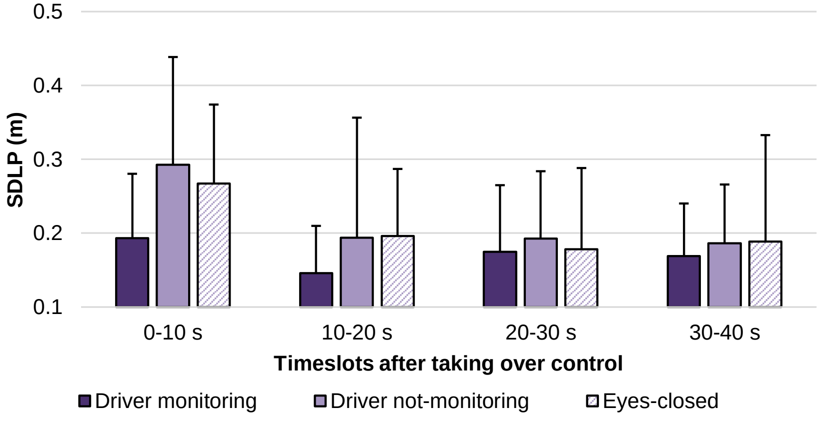


Figure 3.6: Average standard deviation of lateral position (SDLP) for the first 40 s after control was transferred back to the driver. The error bars represent the standard deviations.

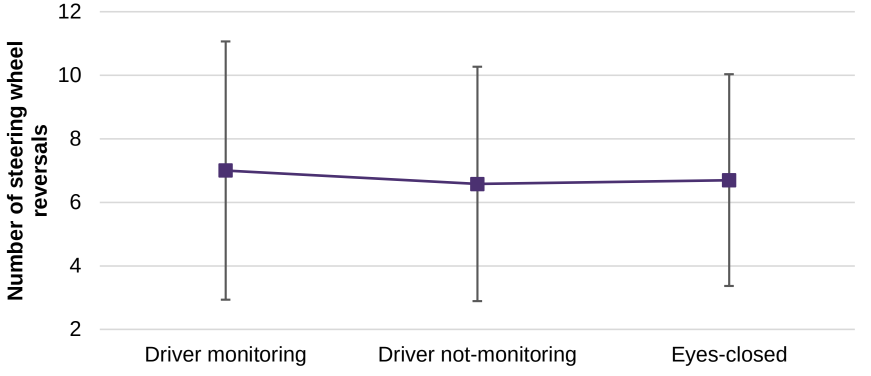


Figure 3.7: Number of steering wheel reversals (>3 deg) for the first 40 s after control was transferred back to the driver. The error bars represent the standard deviations.

Figure 3.8 and Figure 3.9 show longitudinal driving performance with respect to the longitudinal speed and its standard deviation. A main effect of *time* was found for speed ($F(3, 63) = 29.58$; $p < .001$, $\eta^2 = 0.59$), but there was no main effect of task conditions ($F(2, 42) = 2.89$; $p = .66$, $\eta^2 = 0.12$). The speed dropped significantly between 10 s and 20 s after the transition of control (from 21.71 m/s to 21.24 m/s averaged over all conditions), and increased again afterwards. Pairwise comparisons revealed that participants drove at the lowest speed in the Driver Not-monitoring condition, but only for the first 20 s. No differences were found between the other two task conditions.

Main effects of both *task conditions* ($F(2, 42) = 4.97$; $p = .01$, $\eta^2 = 0.19$) and *time* ($F(3, 63) = 50.96$; $p < .001$, $\eta^2 = 0.71$) were found for the standard deviation of the speed. The variability in speed was significantly larger for the first 10 s, after which the drivers in all task conditions were driving at a more consistent speed. The differences between task conditions only lasted for 10 s, with the deviation in speed in Driver Monitoring condition significantly smaller compared to the other task conditions. No significant differences were found between Driver Not-monitoring and Eyes-closed conditions for any of the timeslots.

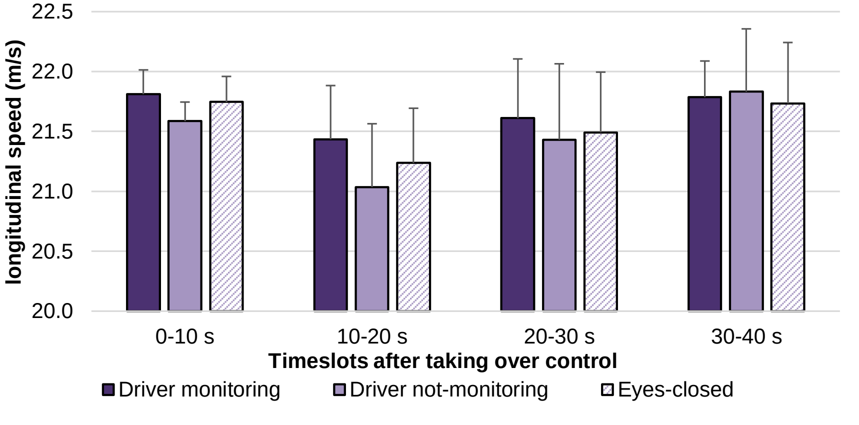


Figure 3.8: Average longitudinal speed for the first 40 s after control was transferred back to the driver. The error bars represent the standard deviations.

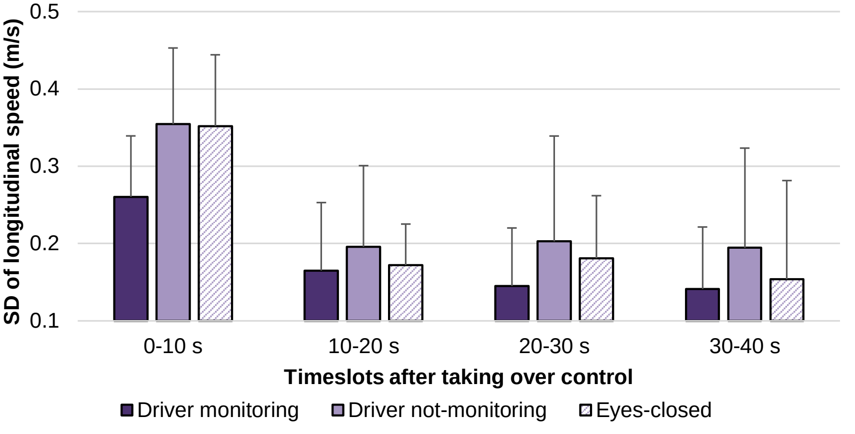


Figure 3.9: Average standard deviation of longitudinal speed for the first 40 s after control was transferred back to the driver. The error bars represent the standard deviations.

Figure 3.10 shows how participants regulated the following distances for the first 40 s after the transition of control. A repeated-measures ANOVA revealed main effects of both *task conditions* ($F(2, 42) = 4.38$; $p = .019$, $\eta^2 = 0.17$) and *time* ($F(3, 63) = 131.74$; $p < .001$, $\eta^2 = 0.86$). Post hoc tests showed that the following distance continued to increase as time passed by, and that participants in the Driver Monitoring condition drove with significantly smaller following distance compared to the other two conditions except for the first timeslot. In order to know when the driver stopped increasing the distance to the lead truck, we conducted a further observation until 120 s after leaving the platoon. No significant differences between timeslots were found from 90 to 100 s, and the time headway came to a stable status at around 2.7 s.

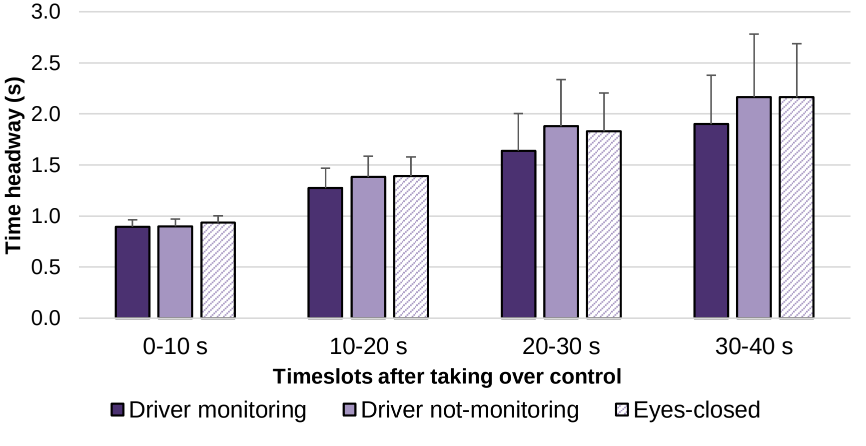


Figure 3.10: Average time headway for the first 40 s after control was transferred back to the driver. The error bars represent the standard deviations.

3.3.3 Driver response in the brake event

In the two trials with brake events, all participants braked in response to the decelerating lead truck with an average brake RT of 1.07 s (*SD* = 0.36 s). No collisions occurred. Paired samples t-tests were conducted to examine whether significant differences existed when comparing the three performance measures between the two task conditions (Table 3.2). Despite of the slight tendency of a better performance in the Driver Monitoring condition, the differences didn't reach the significance level.

Table 3.2: Means and standard deviations of the performance measures in the two task conditions, as well as results of the paired t-tests between conditions.

	Driver Monitoring		Driver Not-monitoring		Paired t-test		
	M	*SD*	*M*	*SD*	*t*	*df*	*p*
Brake RT (s)	1.02	0.22	1.16	0.45	-1.14	21	0.267
Minimum TTC (s)	2.41	0.83	1.99	0.79	2.01	21	0.057
Minimum THW (s)	0.60	0.13	0.57	0.21	1.19	21	0.248

3.4 Discussion

This study mainly investigated driver perception-response times to take over control from highly automated truck platooning systems in normal, non-critical operation. We studied how this take-over process was influenced by three task conditions, namely when the driver was monitoring the road, when working on a hand-held tablet, and when resting with the eyes closed. In general, results show that most participants (95% as mentioned in Section 3.3.1) could indicate their readiness to take over manual control within 8.5 s regardless of the task conditions. When comparing with the non-critical take-over times of passenger car drivers measured in Eriksson and Stanton (2017), the median take-over times in the current study with truck drivers were 1.7 s and 0.7 s shorter in monitoring and visually distracted conditions, respectively. Several factors may contribute to the differences. First of all, the small time gap to the lead truck may lead to shorter take-over times. Because the front view of the ego lane was largely blocked by the lead truck, the driver in the truck platoon could not perceive as much traffic environment as in a passenger car that is not in a platoon (Zhang et al., 2017), which may reduce the information processing time. The small time gap might also lead to a higher risk perception, prompting the driver to respond faster (cf. Summala, 2000). Moreover, the take-over time was measured until the first intervention (steering or braking) of the participants in Eriksson and Stanton (2017), while in the current study the participants pressed a button to resume control. The decision making time to determine a proper intervention may contribute to the longer take-over time in Eriksson and Stanton (2017). In addition, our study utilized within-study design with short automation duration for each trial, whereas in Eriksson and Stanton (2017), between-study design was adopted. Repeated scenario exposure and the expectancy on the upcoming event could have led to shorter RTs (Engström, Aust, & Viström, 2010; Green, 2000; Zhang et al., 2019).

Similar mean take-over times were found in the Driver Not-monitoring condition and the Eyes-closed condition, both significantly longer than the Driver Monitoring condition. On a closer examination, different RT patterns were revealed. In the Driver Not-monitoring condition, the longer total take-over time was mainly due to the increase in the hand movement RT rather than the perception RT. This is in line with previous findings that holding a hand-held device increased the take-over time largely by approximately 1–2 s compared to using a hand-free device in car drivers (Wandtner et al., 2018; Zeeb et al., 2017). With respect to the Eyes-closed condition, the perception RT was the longest among all task conditions, but the hand movement RT was shorter compared to the Driver Not-monitoring condition due to the absence of a hand-held tablet. The outliers with extremely large perception RT values also occurred in the Eyes-closed condition, possibly due of the tendency of drowsiness. We observed that one participant seemed to have fallen asleep at the moment of the TOR onset, and seemed confused for the first few seconds after ‘‘waking up”. It is therefore noteworthy that merely closing the eyes does not emulate sleeping, and caution should be made when interpreting the results obtained from such conditions. Worse situations could occur to fatigued drivers who are deeply asleep during automated driving. Multi-step warning systems can be particularly beneficial for sleeping drivers to get back into cognition loop gradually without causing startling effects. Another possible explanation for the slow perception response is that drivers with eyes closed could only rely on the auditory channel to perceive the warning signal, and thus the effect of the multimodal TOR was reduced (Baldwin & Lewis, 2014; Bazilinskyy & De Winter, 2015). In the other conditions, participants could also see the visual signals through their peripheral vision.

In addition, we found higher movement RTs than perception RTs in all task conditions. This differs from the previous findings in manual driving context, whereby the movement RT is normally much shorter than the perception RT (Green, 2000). When driving in an automated vehicle, it would take on average 1.7 s for truck drivers to replace their hands at the steering wheel at a comfortable pace without non-driving tasks, which could be more than 2.5 times longer when drivers were engaged in non-driving tasks with hand-held devices. The variability in movement RT is also suggested to be the main cause for the individual differences in total take-over times. On a closer examination, we observed the postures of the participants at the moment of TOR onset, as well as their activities during the take-over process. Four typical activities were extracted and further combined with the conditions in which one particular activity occurred. The hand movement RTs in the corresponding trials are shown in Table 3.3. In all Driver Monitoring trials and 12 (out of 18) Eyes-closed trials, participants directly moved their hands to the steering wheel without any intermediate activities. The RT to complete this simple process was the shortest, also with the smallest variability. When participants had to put away the hand-held device in order to take over control, this RT was increased by approximately 2.5 s. In two Driver Not-monitoring trials, the participants also had to put on/off their glasses to switch to driving tasks. This behaviour caused approximately 1 s extra movement time in addition to putting away the tablet only. Moreover, we discovered that in six Eyes-closed trials the participants leaned backwards to rest comfortably during automated driving, and had to adjust the seat position to be able to take over control, resulting in a large mean movement RT of 5.68 s. The variability in physical activities during the take-over process considerably influenced the take-over times.

Table 3.3 Activities performed by the participants during the taking over process

pre-TO Activities	Description	Occurrence number	Condition	MPT (s)	
				Mean	SD
Direct hand-on	The participant directly pressed the button without any intermediate activities.	30	All Monitoring Eyes-closed (12/18)	1.99	0.87
Put away tablet	The participant put away the hand-held tablet before pressing the button.	15	Not-monitoring	4.50	1.37
Put away tablet + glasses	The participant put away the hand-held tablet, and put on/off the glasses before pressing the button.	2	Not-monitoring	5.42	1.35
Adjust the seat	The participant adjusted the seat before pressing the button.	6	Eyes-closed	5.68	1.28

With respect to driving performance after the transition, the differences between the task conditions mainly persisted for the first 10 s, with the performance in the Driver Monitoring condition being slightly better compared to the other task conditions. Such differences between conditions disappeared when more time passed by. Driving performance with respect to SDLP, longitudinal speed and its standard deviation was stabilized within 20 s after the transition. Overall, participants could safely stabilize the truck after leaving the platoon in all task conditions. In the additional trials with brake events, all participants were able to respond quickly to avoid collisions with the decelerating lead truck, with no significant differences in performance between task conditions. Participants' take-over times were suggested to represent the time they need to get ready for normal, uncritical transitions, and be prepared for moderately complex driving situation after the transition.

There are several limitations to be discussed. First, this study focused on non-critical transitions, and participants only needed to stabilize the vehicle or respond to a brake event after leaving the platoon, which may require relatively low cognitive and physical load. The perception RT only concerned the time it takes to sense the TOR and interpret its meaning, which cannot reflect the time to build up adequate situation awareness, as mentioned previously. Therefore, caution should be exercised when generalizing the outcomes to highly complex and unexpected scenarios, which involve high hierarchical level of control tasks (e.g., respond to an unexpected traffic accident, see Michon, 1985). Zhang et al. (2017) focused on the critical transition trial in which participants had to take over control upon an unexpected system failure and avoid collisions with a suddenly exposed stationary truck. All participants could take over successfully without causing an accident, suggesting that they were capable to handle even more critical events. However, no non-driving tasks were permitted in this critical trial and the results may only apply for drivers that are still in the loop. Future studies could implement a larger variety of scenarios and task conditions, and investigate drivers' take-over performance in more complex situations. Second, the duration of non-driving task engagement was short (8 min). The participants were free to choose how to interact with the tablet and no highly cognitively demanding tasks were instructed to be performed. These factors may generate better take-over performance compared to that measured after prolonged automated drives and after being engaged in intensive cognitive tasks. Third, the utilization of a within-subject design may increase familiarization and expectancy, and generate shorter RTs. Moreover, our study was conducted in a driving simulator, which generally raises the issues of ecological validity such as reduced risk perception, simplified driving environment and reduced workload (Carsten & Jamson, 2011; De Winter, Happee, Martens, & Stanton, 2014; De Winter, Van Leeuwen, & Happee, 2012; Eriksson, Banks, & Stanton, 2017; Godley, Triggs, & Fildes, 2002; Green, 2000). However, several studies have found relative validity and sometimes even absolute validity, depending on the type of simulator (Kaptein, Theeuwes, & Van der Horst, 1996; Riener, 2010; Risto & Martens, 2014). The high-fidelity driving simulator used in our study is designed to generate high behavioural validity.

3.5 Conclusion

This study mainly aims to investigate how long it takes truck drivers to get ready to leave a truck platoon in normal operations and how the take-over process is influenced by three task conditions: monitoring the driving environment, interacting with a hand-held tablet, and relaxing with the eyes closed. Additionally, we explored if drivers could cope with a brake event immediately after taking over control. The positive results suggested a sufficient readiness level for moderately complex driving situations.

We found substantial differences in take-over times between the task conditions and large variability between the individual drivers. By exploring perception-response times instead of merely total take-over times, we found different RT patterns for different task conditions. After interacting with a hand-held tablet, the increase in the total take-over time was mainly caused by the hand movement RT to put away the tablet, whereas after relaxing with eyes closed, both longer perception- and movement RTs contributed to the longer total take-over time. Furthermore, the hand movement RT contributed to the total take-over time to a larger extent compared to the perception RT, which can be mainly explained by drivers' activities to resume physical readiness. The results suggest the importance of adaptive approach with personal driver readiness predictors as input parameters for a safe and comfortable transition, and the importance to focus on cognitive and motoric preparation phases before resuming manual control.

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4. Transitions to manual control from highly automated driving in non-critical truck platooning scenarios (with mounted NDT)

Unpublished manuscript.

4.1 Introduction

This study can be seen as a replication of the truck platooning study described in Chapter 3, Both studies used the same truck driving simulator platform and experimental design, but differed in the set-up of the non-driving task performed on the tablet PC. Also, another group of professional truck drivers was invited for this study. In the truck driving simulator study described in Chapter 3, the drivers held the tablet in their hands and were free to interact with it (hand-held). In this study, the tablet was mounted on the centre console (hands-free) and the driver had to perform a standardized visual-motoric task.

This study aims 1) to examine if the findings of the first truck platooning study hold for a different group of professional truck drivers to be generalized to a larger population (replication study), and 2) to investigate the effects of hand-held tablet use compared to hands-free tablet use on drivers' take-over time and take-over quality. The meta-analysis in Chapter 2 pointed out that hand-holding a device is a major determinant of mean take-over response times above many other influential factors, causing an increase of approximately 1 - 1.5 s compared to hands-free task conditions in passenger car studies (e.g., Zeeb, Härtel, Buchner, & Schrauf, 2017; Eriksson & Stanton, 2017; Miller, Sun, Johns, Ive, Sirkin, Aich, & Ju, 2015; Befelein, Naujoks, and Neukum, 2016). Results of the first truck platooning study further revealed a large variation in driver response to put away the tablet PC and to reposition their hands on the steering wheel, which caused a large variation in response times. It is expected that using a mounted tablet could largely shorten the hand movement response time and reduce its variation between drivers. Interestingly, Zeeb et al., (2017) found that using a handheld tablet PC significantly worsened drivers' lane-keeping performance after the transition to manual driving, compared to using a mounted tablet during automated driving. The authors suggested that high motoric task load, such as holding a device in the hands, may impair drivers' take-over quality in lateral vehicle control.

The main aim of this study is to investigated if a similar phenomenon is also found in truck platooning take-over scenarios.

4.2 Methods

4.2.1 Participants

Twenty-three participants (of which 2 females) took part in the experiment. They all held a truck driver's license for at least two years (M = 23 years, SD = 8.8) and drove at least 1000 km per year in a truck (M = 85600 km/year, SD = 42225). On average, the participants were 45 years old (SD = 8.1), ranging from 27 to 58 years old. The research was approved by the Ethical Committee for participant studies of TNO.

4.2.2 Apparatus

In this experiment, the configuration of the truck driving simulator, the simulation of the two-truck platooning system, and the human-machine interface were identical to the first truck platooning study as described in Chapter 3, and therefore will not be repeated here. Driving performance data related to vehicle motion control and driver response times were recorded by the driving simulator software at a sampling rate of 50 Hz. Three cameras were installed in the truck cabin to observe the drivers' face expression, hand movement, and feet movement, respectively.

4.2.3 Experimental design and test scenarios

Similar to the first truck study, a within-subject design was used and each participant performed eight test trials in different experimental conditions, including two baseline manual driving trials and six non-critical platooning trials. The order of the trials was counterbalanced. In each test trial, the participants drove in the right-hand lane (the slower lane) of a two-lane motorway behind a lead truck that was driving with a speed of 80 km/h. They were instructed to follow this lead truck and not change lanes. There were no entries or exits on the route. Slight curves and surrounding traffic were present to simulate realistic but low traffic volume conditions. The drives were always on the same road layout, but the surroundings were different to simulate a different stretch of road to the driver. Before the formal test, the participants were introduced to the concept of platooning, and practised with activating and deactivating the platooning systems in a six-minute-long training drive.

In the automated trials, the ego truck of the participant followed the lead truck with a time gap of 0.8 s. Four minutes after the scenario started, a visual-auditory take-over request (TOR) was issued and the participants had to disengage the automation and take over manual control by pressing a button normally used for cruise control on the right side of the steering wheel. No time restraints were applied and the participants were instructed to press the button whenever they felt ready to resume manual control. After the transition, the participants drove manually for another 2.5 minutes until the end of the scenario.

During the automated driving, the participants were instructed to either monitor the driving situation, or perform a visual-motoric task '*Arrows*' (Engström, Johansson, & Östlund, 2005), or relax with their eyes closed. Performing a standardized task instead of freely using the tablet controlled for workload and allowed for measures of task involvement. Each task condition was assigned to two test trials. The *Arrows* task was performed on a tablet PC mounted on the centre console of the cabin. On the touch screen, metrics (5×5) of arrows were presented with or without a target arrow pointing upwards (among arrows pointing left or right, see Figure 4.1 as an example). The participants determined whether the target arrow was present, and gave their answers by pressing ''yes'' or ''no'' on the touch screen. After providing the answer, a new metric was presented automatically.

In one of the two trials within the same task condition, a brake event was implemented immediately after the control transition. The lead truck braked at the deceleration rate of 5 m/s^2 for 2 s immediately after the driver pressed the button to switch off the automation. The participants had to brake in time to avoid a collision. This was identical to the first truck study.

In the baseline (manual driving) trials, the participants followed the lead truck manually without any assistance from the automation system during a six-minute trial. In one of the trials, the same brake event as described above was implemented five minutes after the scenario started. Table 4.1 shows an overview of all test conditions analysed in this study.

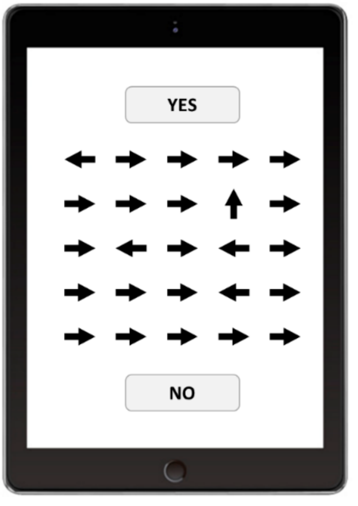


Figure 4.1: Metrix of arrows with a target arrow pointing upwards.

Table 4.1: Overview of test conditions analysed in this study.

Condition	**Task during AD**	**Brake event**	**Duration (min)**
1 (MD)	-	no	6
2 (MD)	-	yes	6
3 (AD)	Monitoring	no	4 (AD) + 2.5 (AD)
4 (AD)	Monitoring	yes	4 (AD) + 2.5 (AD)
5 (AD)	Arrow task	no	4 (AD) + 2.5 (AD)
6 (AD)	Arrow task	yes	4 (AD) + 2.5 (AD)
7 (AD)	Eyes closed	no	4 (AD) + 2.5 (AD)
8 (AD)	Eyes closed	yes	4 (AD) + 2.5 (AD)

4.2.4 Dependent variables

Driver take-over response times, post-transition manual driving performance, and response times and response quality in the brake event were analysed and compared between task conditions. To analyse drivers' take-over process, the total take-over response time (TRT), the perception response time (PRT), and the hand movement response time (MRT) were measured in the same manner as in the first truck platooning study. TRT was defined as the time interval between the onset of the TOR until the moment when the participant pressed the button to reclaim control. PRT was measured from the onset of the TOR until the start of the participant's hand movement to grasp the steering wheel, indicating the time elapsed to perceive and understand the necessity to take over control. MRT was the remaining time measured until the driver pressed the button, indicating the time elapsed to regain motoric readiness for manual driving. Participants' body postures at the TOR onset, and activities during the take-over process were logged from the video recordings by two annotators. A high degree of reliability between the observers was found (the average intraclass correlation coefficient (ICC) was 0.955 with a 95% confidence interval from 0.943 to 0.965). All take-over response time measures were analysed for experimental trials without brake events.

For the trials without brake events, drivers' post-transition manual driving performance was assessed in terms of standard deviation of lateral position (SDLP), the mean and standard deviation of longitudinal speed, and the mean time headway (THW). Results of the first truck experiment showed that SDLP and speed related performance were stabilized within 10- 20 s after the transition, while the THW continued to increase until 90 – 100 s after the transition. In this study, we therefore analysed the SDLP, and mean and standard deviation of longitudinal speed in time windows of 10 s for 40 s after the control transition. THW was observed until 120 s after the control transition. SDLP and THW were also compared to the performance measures in the baseline manual driving condition to explore carry-over effects of platooning, as suggested in Skottke, Debus, Wang, and Huestegge (2014). The observation time window in the baseline condition was 4.5 minutes after the scenario start during 40 s and 120 s.

For the trials with brake events, we measured brake response times, minimum time-to-collision, and maximum deceleration rate to evaluate participants' response to the braking lead truck. Brake response time was defined as the time interval between the activation of the brake lights of the lead vehicle and the moment when the driver pressed the brake pedal.

4.3 Results

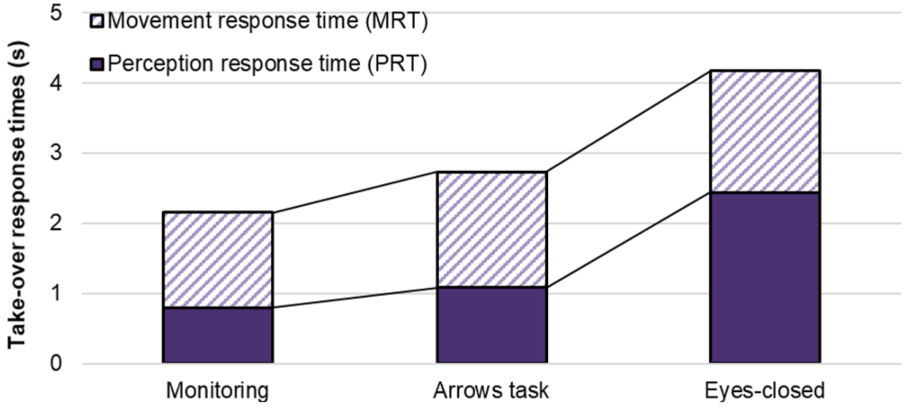
Since the data of the first participant were lost, the data of 22 participants were analysed. Eight trials divided over six participants were excluded from the analysis of take-over response times due to missing video recordings (in five platooning trials) or participants not obeying the instructions (starting manual driving before pressing the button, in three platooning trials). Data from all trials were valid for the analysis of post-transition manual driving performance. All statistical analyses were conducted using SPSS 24. The significance level used was 0.05.

4.3.1 Take-over response times

An overview of drivers' take-over response times measured in three task conditions is shown in the stacked bar plot (Figure 4.2). The descriptive data of the three response time measures are presented in the table below.

The total take-over times ranged from 0.9 s to 13.27 s (on average 2.99 s) combining all task conditions. Results of Friedman tests indicated significant differences in TRT ($\chi^2(2) = 21.50$, p <.001), PRT ($\chi^2(2) = 20.67$, p <.001), and MRT ($\chi^2(2) = 8.00$, p <.02), between the three task conditions. Post-hoc Wilcoxon signed-rank tests using a Bonferroni-Holm correction revealed that differences in TRTs were significant between each of the two task conditions (*Monitoring* vs. *Arrows task*: p = .005; *Monitoring* vs. *Eyes-closed*: p <.001; *Arrows task* vs. *Eyes-closed*:

p = .022), which is also the case for PRTs (*Monitoring* vs. *Arrows task*: p = .019; *Monitoring* vs. *Eyes-closed*: p <.001; *Arrows task* vs. *Eyes-closed*: p = .011). Significant differences in MRTs were only found between the *Monitoring* condition and the *Eyes-closed* condition (p = .003). Additional pairwise comparisons were conducted to compare PRTs and MRTs in each task condition. Results showed that MRTs were significantly larger than PRTs in the *Monitoring* condition (p = .002) and the Arrows test condition (p = .005). No significant differences between PRTs and MRTs in the *Eyes-closed* condition were indicated.



	Mean (SD)	Median	Min.	Max.	IQR
PRT					
Monitoring	0.80 (0.38)	0.80	0.20	1.93	0.42
Arrows task	1.08 (0.43)	0.97	0.62	2.52	0.45
Eyes-closed	2.44 (2.98)	1.16	0.58	11.73	1.46
MRT					
Monitoring	1.36 (0.61)	1.33	0.30	3.03	0.71
Arrows task	1.64 (0.86)	1.46	0.81	4.48	0.52
Eyes-closed	1.73 (0.53)	1.64	0.82	2.89	0.66
TRT					
Monitoring	2.16 (0.81)	2.09	0.90	4.13	0.92
Arrows task	2.73 (1.05)	2.43	1.66	6.11	0.75
Eyes-closed	4.16 (3.10)	2.87	1.70	13.27	2.61

Figure 4.2: Driver take-over response times in seconds across the three conditions. The bars show the means of MRTs and PRTs per condition. They add up to the TRTs. IQR = Interquartile range.

4.3.2 Post-transition manual driving performance

Three 3 × 4 repeated measures ANOVA were performed to examine the effects of *task* conditions and *time* elapsed after the transition on drivers' SDLP, mean longitudinal speed, and standard deviation of longitudinal speed, respectively. With respect to SDLP (Figure 4.3), there were a significant main effect of *time* (F (3, 63) = 7.64, p <.001, η^2 = .27), no main effect of *task*, and a significant interaction between *task* and *time* (F (6, 126) = 3.41, p = .004, η^2 = .14). Post-hoc pairwise comparisons revealed a significantly higher SDLP in the first 10 s in the *Monitoring* condition. No differences between timeslots were found in the other two conditions. When comparing between task conditions, no significant differences were found in any timeslots. Additionally, we compared the post-transition SDLP to that measured in the baseline (manual) driving condition. Post-transition SDLP was significantly higher than baseline SDLP only in the first 10 s in the *Monitoring* condition.

Figure 4.3: Mean standard deviation of lateral position (SDLP) in the first 40 s after the control transition back to the driver measured in three task conditions (purple bars) and the baseline driving condition (the grey bar). The error bars represent the standard deviations.

Figure 4.4 and Figure 4.5 depict drivers' performance with respect to longitudinal speed and its variation. When examining the effects on longitudinal speed, we found significant main effects of both *task* (F (2, 42) =5.84, p =.006, η^2 = .22) and *time* (F (1.69, 35.54) = 27.66, p <.001, η^2 = .57, degrees of freedom adjusted using Greenhouse-Geisser estimates of sphericity), but no significant interaction between the main effects. Post-hoc pairwise comparisons showed that the mean speed significantly decreased in the first 20 s after the transition, and gradually increased between 30 – 40 s. Effects of *task* conditions became noticeable from 10 s after the transition: Participants drove with a significantly lower mean speed in the *Arrows task condition* and the *Eyes-closed* condition compared to the *Monitoring* condition.

There was a main effect of *time* (F (3, 63) = 59.16, p <.001, η^2 = .74) on the variation in longitudinal speed. The main effect of *task* and the interaction between the main effects were not significant. Post-hoc pairwise comparisons showed that the variation in speed significantly decreased in the first 20 s and came to a stable status in the following timeslots.

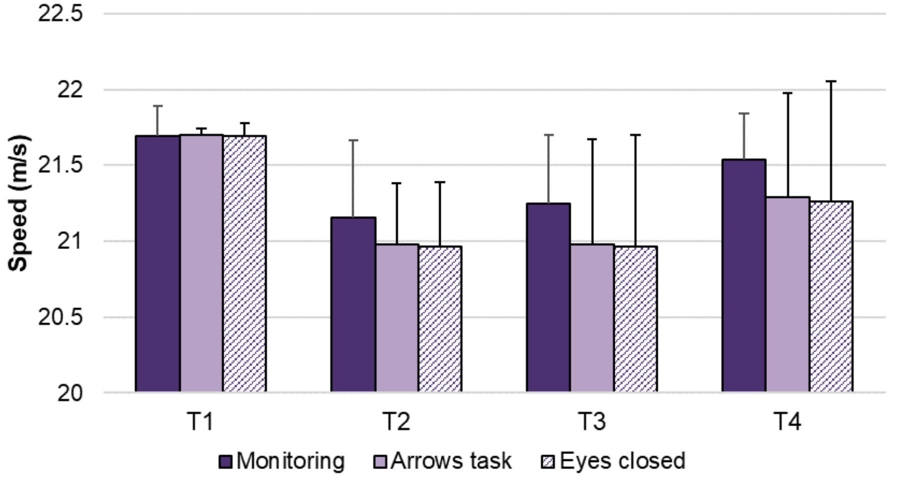


Figure 4.4: Mean longitudinal speed in the first 40 s after the control transition back to the driver. The error bars represent the standard deviations.

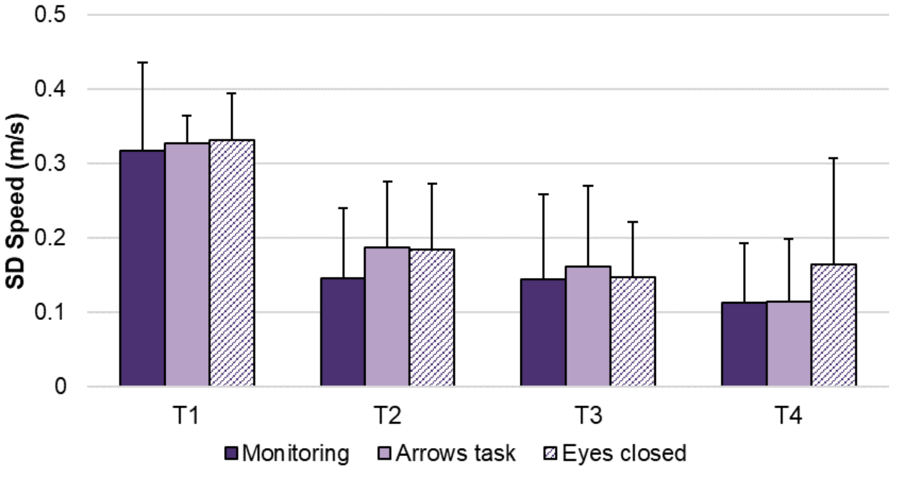


Figure 4.5: Mean standard deviation of longitudinal speed in the first 40 s after the control transition back to the driver, measured in three task conditions. The error bars represent the standard deviations.

With respect to the regulation of the following distance (Figure 4.6), a 3 × 12 repeated measures ANOVA showed significant main effects of *task* (F (2, 42) = 4.94, p =.012, η^2 = .19) and *time* (F (1.43, 29.96) = 55.64, p <.001, η^2 = .73). The interaction between the main effects was marginally significant (F (3.30, 69.36) = 55.64, p = .087, η^2 = .10). The degrees of freedom for *time* and the interaction were adjusted using Greenhouse-Geisser correction due to the violation of sphericity. Post-hoc pairwise comparisons revealed that in the *Monitoring* and *Eyes-closed* conditions, THW continued to increase until 70 - 80 s after the control transition. In the *Arrows task* condition, a significant increase in THW was not observed after 50 – 60 s. Differences between task conditions were observed between 40 s to 100 s after the control transition. THW in the *Monitoring* condition was significantly lower than the other two conditions between 40 – 60 s. From 60 s to 100 s, significant differences only existed between the *Monitoring* and the *Eyes-closed* conditions. THW in the *Arrows task* and the *Eyes-closed* conditions did not differ significantly in any of the timeslots, despite the tendency of a higher THW in the *Eyes-closed* condition. We performed additional pairwise comparisons to examine the carry-over effects of platooning on THW, and found that the post-transition THW in the *Monitoring* and the *Arrows task* conditions were significantly lower than the baseline TWH throughout the observation window. In the *Eyes-closed* condition, significant differences between the post transition THW and the baseline THW disappeared 80 – 90 s after the transition.

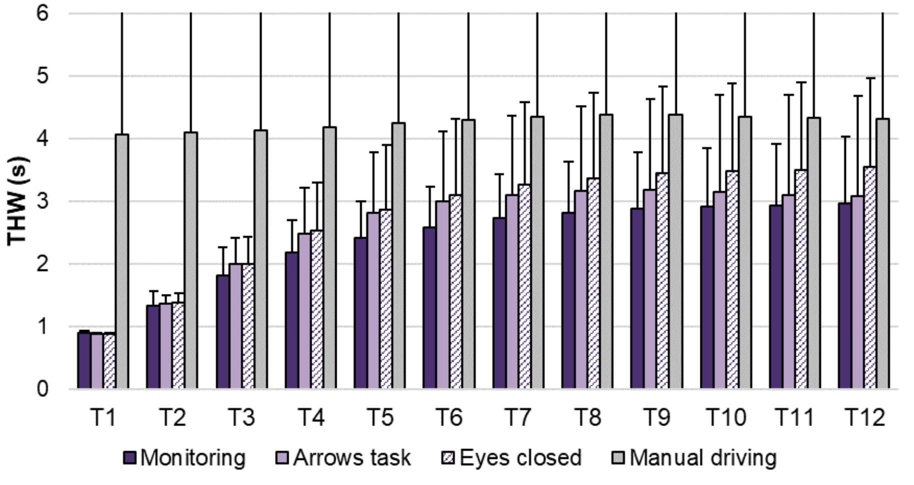


Figure 4.6: Mean time headway (THW) in the first 120 s after the control transition back to the driver measured in three task conditions (purple bars) and in the baseline driving condition (the grey bar). The error bars represent the standard deviations.

4.3.3 Response in the post-transition brake event

In response to the brake event immediately after the control transition, one participant collided with the decelerating lead truck in the initial *Eyes-closed* condition due to late response. Minimum TTC and maximum decelerating in this trial were therefore not included in the analysis, although interesting from an outlier and traffic safety perspective. Three one-way repeated measures ANOVA were performed to compare brake response times, minimum TTC, and maximum deceleration between task conditions. The main effect of task conditions was not significant with respect to any of the performance measures. Table below showed the descriptive statistics and the results of the ANOVAs.

Table 4.2: Means and standard deviations of the brake response measures, as well as the results of repeated measure ANOVAs.

	Monitoring	Arrows task	Eyes-closed	Repeated measures ANOVA			
	M (SD)	M (SD)	M (SD)	*F*	*df*	*p*	η^2
Brake response time (s)	1.09 (0.36)	1.02 (0.34)	1.19 (0.38)	1.22	2, 42	n.s.	.06
Minimum TTC (s)	2.50 (1.05)	2.85 (1.25)	2.55 (1.23)	0.60	2, 40	n.s.	.03
Maximum Deceleration (m/s^2)	5.66 (0.87)	5.75 (0.82)	5.94 (0.70)	1.79	2, 40	n.s.	.08

4.4 Discussion

4.4.1 Take-over response times

Take-over response times showed significant differences between the three conditions. The *Monitoring* condition yielded the shortest mean total response time, followed by the *Arrows task* condition and the *Eyes-closed* condition. In line with the first study, hand movement time was longer than the perception time except for the *Eyes-closed* condition, in which the perception time increased largely and did not show significant difference compared to the hand movement time. In both experiments, extremely long take-over times (outside the 95th percentile, i.e., larger than 8.6 s) were all generated in the *Eyes-closed* condition, by participants seemingly fallen asleep when the TOR was issued.

As expected, the effect of hand-held or hands-free tablet use showed a large impact on take-over times when comparing between the two studies. When performing a task on a mounted tablet instead of holding the tablet in the hands, truck drivers took over on average 2.8 s faster with a smaller variation. This was mainly due to the largely reduced hand movement time while using the mounted tablet (3 s faster than the hand-held condition in Chapter 3), which no longer significantly differed from the hand movement time in the *Monitoring* condition. Also worth noting was that drivers' perception time while performing the *Arrows* task was significantly longer than the *Monitoring* condition. In the first study, drivers did not show increased perception time when freely interacting with the tablet compared to monitoring the driving situation. It could be that the standardized task in the second experiment required more engagement and generated a higher level of workload than naturalistic task (Shinar, Tractinsky, & Compton, 2005). Another possible explanation is that participants might have checked the driving situation less frequently when performing the *Arrows* task (the next level automatically started after giving the answer) than using the tablet freely, which negatively influenced take-over response times (Zeeb, Buchner, & Schrauf, 2015).

4.4.2 Post-transition manual driving performance

In line with the first study, drivers in all task conditions could stabilize the lateral and longitudinal vehicle motion within 10 – 20 s after the control transition, seeing that the SDLP and the variation of longitudinal speed no longer significantly varied in the successive timeslots (Figure 4.3, Figure 4.5). In the first study, drivers showed worse lane-keeping performance in the *Tablet* and the *Eyes-closed* conditions compared to the *Monitoring* condition in the first 10 s after the transition, which was not observed in this study. It could be that using a mounted tablet instead of a handheld tablet reduced motoric task load and led to a better steering performance immediately after the transition (the mean SDLP was 0.12 m smaller), as suggested in Zeeb et al., (2017). Nevertheless, this could not explain the differences between the two studies regarding the *Eyes-closed* condition (i.e., the differences could be merely by chance). More studies are needed to examine the relation between motoric task load and take-over quality in lateral control for valid conclusions.

Truck drivers in both studies showed similar behaviours in regulating the longitudinal speed and the following distance after the control transition. Drivers reduced the speed within the first 20 – 30 s to rapidly increase the THW, then gradually increased the speed in the following timeslots. The mean THW continued to increase until 1 – 1.5 minutes after the transition, then reached a relatively stable status. The carry-over effect of platooning on THW was still significant two minutes after the control transition, particularly in the *Monitoring* and the *Tablet* conditions. It has to be noted that the baseline manual driving THW was generated in low-volume traffic conditions, which is usually 1-2 s higher than that measured in high-volume traffic conditions (Ayres, Li, Schleuning, & Young, 2001). Within two minutes after the transition, THWs in all conditions surpassed the safe time headway requirement of 2 s, and can be considered acceptable even though they still appeared lower than the baseline THW. Results of both studies also pointed to the tendency of a lower post-transition THW in the *Monitoring* condition. The carry-over effect appeared to be stronger when drivers were monitoring the lead truck during the platooning, and therefore may have visually adapted to the small gap between vehicles.

4.4.3 Performance in the brake event

When examining drivers' response in the brake event immediately after the control transition, no significant differences in brake response times, minimum TTC, and maximum deceleration were found between the monitoring and the tablet conditions, in line with the findings of the first study. Also noteworthy was that one crash occurred in the *Eyes-closed* condition, but not in the other task conditions. This finding, together with the high perception take-over response times generated in this condition, suggested that resting with eyes closed impairs drivers' cognitive performance when resuming manual control from automated driving.

4.5 Conclusion

In general, the findings of this replication study are in line with the results of the first truck platooning study, except for the differences related to the tablet PC. Using a mounted tablet PC instead of holding the device in the hands largely reduced the hand movement response time and its variation between drivers, and therefore largely reduced the total response time. Drivers should not be allowed to use handheld device if the take-over situation can be urgent. The results of this study also suggested that using a handheld tablet may impair lane-keeping performance after taking over control. Further research is needed to draw generic statements and conclusions for a larger truck driver population. This study also pointed to the potential risk of resuming manual driving after sleeping or relaxing with eyes closed. Extra efforts should be made to either prevent truck drivers from sleeping, or to allow this only in case that safe platooning over longer periods of time could be guaranteed. However, it should be carefully taken into account that more research would need to be done to assist these drivers with a smooth transition and a rapid resumption of situation awareness and cognitive performance after having rested with their eyes closed.

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5. Taking back manual control after automated platooning: A comparison between car and truck driver's behaviour

This chapter is based on Zhang, B., Hogema, J. H., Willemsen, D. M. C., Wilschut, E. S., & Martens, M. H. (2020). *Taking back manual control after automated platooning: A comparison between car and truck driver's behaviour.* Under review.

5.1 Introduction

Thanks to the rapid advancement of technology, intelligent transport systems and advanced driver assistance systems are undergoing an intense development. Cars with automated functions that predominantly rely on on-board sensory systems are already available on the consumer market. Meanwhile, connected and automated vehicles (CAV) with advanced communication technologies are drawing more and more attention for their potential to improve road safety, traffic flow, and energy efficiency (Coppola & Silvestri, 2019; Rios-Torres & Malikopoulos; 2017, Talebpour & Mahmassani, 2016; Shladover, 2018). Combining Vehicle to Vehicle (V2V) and Vehicle to Infrastructure (V2I) communication with on-board control units, CAVs are able to exchange real-time traffic information and make immediate adjustment to the dynamics of other connected vehicles, and travel smoothly with a much shorter following distance compared to regular manually driven vehicles and stand-alone automated vehicles (Coppola & Silvestri, 2019; Shladover, 2018; Talebpour & Mahmassani, 2016).

In recent decades, technical research and development on CAVs mainly focused on platooning of heavy-duty trucks, largely driven by the increasing demand for fuel efficient freight transportation (Bhoopalam, Agatz, & Zuidwijk, 2018; Janssen, Zwijnenberg, Blankers, & De Kruijff, 2015; Turri, Besselink, & Johansson, 2016; Tsugawa, 2013). Simulations and field experiments have demonstrated that platooning with a gap between 4 – 10 m could save up to 10% - 20% fuel consumption for the following trucks achieved by reduced aerodynamic drag (Browand, McArthur, & Radovich, 2004; Tsugawa, Jeschke, & Shladover, 2016), and bring immediate profit to freight carriers once adopted (Janssen et al., 2015). During the European Truck Platooning Challenge in April 2016, truck platoons with automated longitudinal control were brought onto public roads for the first time while crossing international borders, showing the technical and commercial feasibility of platooning technology. Besides truck platoons, passenger car platoons and heterogeneous platoons consisting of heavy vehicles and passenger cars are also realistic use cases when operating platoons in general traffic (Bergenhem, Huang, Benmimoun, & Robinson, 2010; Bergenhem, Shladover, Coelingh, Englund, & Tsugawa, 2012), which receive less attention due to a slower return on investment (Tsugawa et al., 2016; Janssen et al., 2015).

5.1.1 Human driver’s role in platooning

Various platooning concepts have been discussed and developed that operate at different levels of driving automation. The role and responsibility of the driver also vary. A widely adopted platooning concept is to manually drive the lead vehicle by a professional truck driver, while other vehicles follow automatically with a professional driver at the driving seat, connected and coordinated through wireless communication and radar technology such as Cooperative Adaptive Cruise Control (CACC, Ploeg, Van de Wouw, & Nijmeijer, 2014). In order to come together and get in the right platooning conditions, all vehicles still need to be manually driven. Thus, platoons can be operated on existing road infrastructures without the need of dedicated lanes.

In the early development phase and in many demonstrations on public roads, platooning systems only enabled longitudinal automation of the following vehicles, while steering was still executed by human drivers (Level 1 driving automation according to SAE taxonomy, 2018). At the current stage, partial automated platoons that execute both lateral and longitudinal vehicle control under constant supervision of the driver (SAE Level 2) have been realized on test tracks, and are expected to be commercialized as a next stage (Janssen et al., 2015). Experts have expressed concerns regarding this level (Kyriakidis et al., 2019; Norman, 2015; Onnasch, Wickens, Li, & Manzey, 2014) because humans are naturally poor at prolonged monitoring tasks (Davies & Parasuraman, 1982; Mackworth, 1948; Parasuraman 1987; Scerbo, 2001) and it can be very risky for the driver in a platoon to respond to longitudinal critical events due to very short inter-vehicular distances (Nowakowski, Shladover, & Tan, 2015; Willemsen et al., 2018). The long-term goal is to implement highly automated platoons that do not require constant monitoring nor require drivers as emergency backups within the operational design domain (i.e., SAE Level 4). It is generally believed that only at such level could drivers truly benefit from driving automation, because they could make use of the travel time to relax or undertake other non-driving tasks (Kyriakidis et al., 2019; Carsten & Martens, 2018). Transitions of control between the system and the driver would still be expected when forming and dissolving the platoon, and occasionally after the system encounters sensors limitations or an upcoming end of the operational design domain.

5.1.2 Transitions of control and related research

Similar to the introduction of cars with automated functions, the deployment of platooning technology on public roads is likely to go through several intermediate phases. As long as human involvement is still required, the human-system interaction involving various types of platoon drivers would need to be a major research focus. The transition of control from the automation function back to the driver, also known as driver take over, is widely recognized as a critical phase where adverse situations may occur (for an overview, see Lu, Happee, Cabrall, Kyriakidis, and De Winter, 2016). Compared to manual driving, taking back control from automated driving asks for additional information processing tasks, including perception of the stimulus that initiates the transition (usually a take-over request issued by the system, or an event in the environment), comprehending the driving situation and regaining situational awareness, making a decision on what to do, and actually perform the take-over action (braking, accelerating, or steering) after repositioning hands back on the steering wheel and feet back on the pedals (Gold & Bengler, 2014; Zeeb, Buchner, & Schrauf, 2015, 2016). The key to a successful control transition is to complete the take-over process with sufficient quality before the driver loses control of the situation, thereby avoiding collisions or endangerment (Naujoks, Wiedemann, Schömig, Jarosch, & Gold, 2018; Nilsson, Falcone, & Vinter, 2015). To understand how long it takes for a driver to adequately take over control provides important input for the development of safe driving automation systems.

A large number of studies have investigated drivers' take over performance under various conditions, mostly in stand-alone automated car scenarios. To address the essential question of take-over response times, Zhang, De Winter, Varotto, Happee, and Martens (2019) conducted an exhaustive meta-analysis of 129 studies that involved control transition from automated driving to manual (of which three were truck automation studies). Results showed that mean (average over different participants or groups) take-over times reported in the studies vary largely from less than 1 s to above 20 s under the interplay of diverse factors related to the driver, the type of automation, the human machine interface (HMI), and the driving environment. The most significant determinants of the take-over time are the urgency of the take-over situation, whether non-driving tasks are performed on a hand-held device, and familiarization and expectancy with the take-over scenarios. The authors, along with a number of researchers, also cautioned that a short take-over response time alone cannot guarantee safe take-over behaviour. In more urgent situations, drivers tend to respond faster but with lower quality, characterized by a higher accident rate (Mok, Johns, Lee, Miller, Sirkin, Ive, & Ju, 2015), more abrupt manoeuvring of the vehicle (Gold, Damböck, Lorenz, & Bengler, 2013; Ito, Takata, & Oosawa, 2016; Clark & Feng, 2017), and poorer hazard perception (Vlakveld, Van Nes, De Bruin, Vissers, & Van der Kroft, 2018). A widely accepted assumption is that 7 – 10 s is sufficient for distracted drivers to take over in response to a critical event without crashing (e.g., Ito et al., 2016; Melcher, Rauh, Diederichs, Widlroither, & Bauer, 2015; Petermann-Stock, Hackenberg, Muhr, & Mergl, 2013; Walch, Mühl, Kraus, Stoll, Baumann & Weber, 2017). However, Gold et al. (2013) found that given a 7 s time budget, drivers still exhibited more risky evasive manoeuvres with fewer mirror checks compared to the baseline manual driving condition. Eriksson and Stanton (2017) assert that take-over times measured in non-critical scenarios could better reflect the time the driver actually needs to resume control, and applied no time restrictions in their driving simulator study with passenger car drivers. Participants displayed a large variation in take-over times even without performing non-driving tasks, ranging from 1.9 s to 25.7 s. Lu, Coster, and De Winter (2017) explored time required to regain situation awareness when taking over control, and found that up to 20 s may be needed for the participants to sufficiently comprehend the traffic situation presented in the video clips.

Research on driver take-over performance in platooning scenarios has received less attention. A series of driving simulator studies rooted in the German project KONVOI investigated drivers' manual driving performance immediately after decoupling from a highly automated passenger car platoon (Eick & Debus, 2005; Wille, Röwenstrunk, & Debus, 2008; Brandenburg & Skottke, 2014; Skottke, Debus, Wang, & Huestegge, 2014). The results generally pointed to a decrease in time headway (THW) after leaving the automation mode compared to drivers' preferred THW in normal manual driving, which may have been a result of behavioral adaptation to the short gaps as suggested by Martens and Jenssen (2012). In particular, Skottke et al., (2014) looked into the change of THW as a function of time, and found that such carry-over effects lasted for 10 km (approximately 6 minutes). Impaired lane keeping performance (in terms of increased standard deviation of lateral position, SDLP) after leaving the platoon was also observed in these studies. However, Skottke et al., (2014) argued that this might be due to the long time spent in the experiment (time-on-task effect) rather than the effect of automation, since SDLP increased with similar magnitude in the manual driving condition as the same amount of time passed by. In a recent study, Castritius et al. (2020) compared professional truck drivers' pre- and post-platoon manual driving performance under real traffic conditions on public roads (with the THW of 0.6 s or 0.9 s at the speed of 80 km/h). Drivers in the following truck displayed significantly higher SDLP in the post-platooning section, but no significantly differences in THW between the two sections. The authors cautioned that confounding variables induced by the real road setting, such as the behaviour of surrounding road users and traffic volume, might lead to the inconsistency with the previous findings.

Truck platoon drivers' take-over response in critical system failure scenarios was first tackled in the Japanese Energy ITS project (Zheng, Nakano, Yamabe, Aki, Nakahra, & Suda, 2014; Yamabe, Zheng, Nakano, Suda, Takagi, & Kawahara, 2012). In their experiments, participants were instructed to apply emergency braking as soon as the braking light of the preceding truck was activated (with a THW of 0.45 s at a speed of 80 km/h). Results showed an average take-over response time around 0.6 s, and that in this case (the brake response time being larger than the THW during platoon driving) rear-end collisions could only be avoided when the mean maximum deceleration of the following truck was higher than the preceding truck. Response times here were low since drivers needed to stay alert and knew that they would encounter critical events.

In recent years, several studies conducted by TNO systematically researched drivers' take-over performance from highly automated platooning, aiming to provide input for an adaptive control transition approach. Zhang, Wilschut, Willemsen, and Martens (2019) and Wilschut, Willemsen, Hogema, and Martens (2016) reported truck driving simulator findings, in which professional truck drivers performed eight non-critical control transitions to manual driving without time restrictions under three task conditions. Results showed that drivers used significantly more time to take over control when interacting with a hand-held tablet or relaxing with their eyes closed compared to monitoring the road without non-driving tasks. A large variation in drivers' response to reposition hands on the steering wheel was also observed, which in turn led to a large variation in the total take-over times.

5.1.3 Difference between passenger car drivers and professional truck drivers

As platooning technology can be applied to both trucks and cars, it is of interest to explore whether professional truck drivers and non-professional passenger car drivers behave differently in a take-over situation after a platooning drive. Heavy trucks and passenger cars foremost differ in physical and operational characteristics such as size, weight, turning radii, power-to-mass ratio, and acceleration/deceleration capability (Mehdizadeh, Shariat-Mohaymany, & Nordfjaern, 2018; Peeta, Zhang, & Zhou, 2005; Ramsay, 1998). To compensate for the vehicle's relatively poor manoeuvrability, heavy-truck drivers normally drive at a lower speed, exhibit a smoother car-following behaviour with a larger distance to the preceding vehicle, and execute lane-changing manoeuvres more slowly with a lower acceleration or deceleration compared to passenger car drivers (Aghabayk, Moridpour, Young, Sarvi, & Wang, 2011; Durrani, Lee, & Zhao, 2016; Moridpour, Rose, & Sarvi, 2010). When driving behind a heavy truck, both car drivers and truck drivers increase following distances compared to following a passenger car (Aghabayk, Sarvi, & Young, 2012; McDonald, Brackstone, Sultan, & Roach, 1999).

Differences between professional truck drivers and non-professional passenger car drivers also exist in their demographics, skill base, and attitude towards safe driving. Compared to average car drivers, truck drivers are predominantly male, have a higher mean age and higher mean annual mileage, spend more hours in traffic working purposes, and experience more practice and training (Rosenbloom, 2011; Rosenbloom, Eldrorb, & Shahara, 2009). Previous research generally points to a more cautious, less risky driving behaviour among truck drivers compared to car drivers, indicated from self-reporting and analysis of naturalistic driving data (Mehdizadeh et al., 2018; Rosenbloom et al., 2009; Walton, 1999). Truck drivers are less likely to commit errors and violations, and are generally well-trained to avoid dangerous situations (Rosenbloom, 2011). Despite the fact that heavy trucks are disproportionally involved in fatal accidents, the large majority of these fatal accidents were caused by cars (Blower, 1998; Rosenbloom, 2011; Thiriez, Radja, & Toth, 2002).

In the context of automated driving, Zhang, Wilschut et al., (2019) and Lotz, Russwinkel, and Wohlfarth (2019) investigated professional truck drivers' take-over performance and compared this to take over performance reported in published passenger car take-over studies (Eriksson & Stanton, 2017; Damböck et al., 2012; Zeeb et al., 2015; Radlmayr, Gold, Lorenz, Farid & Bengler, 2014; Gold, Lorenz & Bengler, 2014). Both studies suggested a shorter take-over response time among professional truck drivers, possibly explained by their higher level of expertise. Nevertheless, the validity of these findings needs further investigation due to the heterogeneity between the studies for comparison (i.e., differences in factors such as experimental design, instruction, the type of simulator that is driven). For example, truck drivers' faster response observed in Zhang, Wilschut et al., (2019) could be due to the effects of practice and familiarization induced by within-subject design, as compared to Eriksson and Stanton (2017) in which between-subject design was used. To date, we are not able to identify studies that directly compare truck drivers' and passenger car drivers' take-over performance controlling for other experimental variables.

5.1.4 Research objectives

The literature research pointed to the importance of ensuring a safe control transition to manual in the development of driving automation, and the fact that we are still at an early stage of understanding drive behaviour when decoupling from car and truck platoons. To fill in the research gaps and to enrich the literature on human factors research concerning control transitions in platooning scenarios, this study compares professional truck drivers' take-over performance when leaving a highly automated platoon (as reported in Zhang, Wilschut et al., 2019) to that of car drivers measured in the same TNO driving simulator (with a different vehicle mock-up) using the identical experimental design. The main aim of the study was to investigate behavioural similarities and differences between the two driver groups during the decoupling of platoons and in the subsequent manual driving. The results could be a basis for developing efficient manners to support car and truck platoon drivers to resume manual control safely and smoothly. In addition, research shows that changes in vehicle dynamics during control transitions substantially affect traffic flow efficiency (Varotto, Hoogendoorn, Van Arem, & Hoogendoorn, 2015; Varotto, Farah, Bogenberger, Van Arem & Hoogendoorn, 2020). The results of this study could also provide input for modelling the effects of platooning on traffic flow considering the impact of driver behaviours when dissolving the platoon.

5.2 Methods

This paper is based on two separate driving simulator studies conducted in the TNO driving simulator, using an identical experimental design but different simulator configurations (truck and car, with different mock-ups and different vehicle models) and participant groups (truck drivers and car drivers). In the car platooning study, a moving-base car driving simulator experiment was conducted with experienced car drivers. The truck platooning study was a repetition of the car platooning study, with a driving simulator in truck configuration and with professional truck drivers as participants to enable comparisons between the two driver groups. In the following sections, the experimental setup for both experiments are introduced in turn, followed by descriptions of experimental design and dependent measures.

5.2.1 Participants

Eighteen participants were involved in the car platooning study. All participants held a driver's license for at least 2 years and drove at least 10.000 km per year. Their average age was 39.5 years old (SD = 9.6). The group consisted of 11 male and 7 female drivers. None of them had experience in driving a truck.

Twenty-two professional truck drivers participated in the truck platooning study. They all held a truck driver's license for at least 8 years (on average 29 years) and drove in a truck at least 10.000 km per year (on average 35218.7 km/year). The average age of the participants was 47.4 years old (SD = 11.5). The group consisted of 20 male and 2 female drivers. Both experiments were approved by the Ethical Committee for participant studies of TNO.

5.2.2 Apparatus

Both experiments were conducted in the high fidelity moving-base driving simulator with six degrees of freedom, located at TNO, the Netherlands. In the car platooning experiment, a BMW car mock-up (Figure 5.1 Left), and in the truck platooning experiment a DAF truck mock-up (Figure 5.1 Right), was mounted on the moving base. The two experiments used different mathematical vehicle models to represent the dynamics of a passenger car and a truck, respectively. Eye heights in the visualisations were also modified to incorporate the differences between the vehicle categories in this respect. In both experiments, the road and traffic environment were projected on cylindrical screens around the vehicle. Three projectors provided the front view with a horizontal viewing angle of 180 degrees and a vertical viewing angle of 41 degrees (22 degrees above and 19 degrees below the neutral viewing direction). The rear view was realised by two screens placed behind the vehicle for exterior mirrors, and one 32-inch LCD screen placed in the back of the car for the interior rear-view mirror (the interior rear-view mirror was not available in the truck cabin). In the car platooning experiment, the human-machine interface (HMI) presenting the status of the automated platooning system was integrated in the dashboard below the speedometer. In the truck platooning experiment, this interface was displayed on an additional tablet PC mounted close to the centre console. Vehicle related data in both experiments were recorded by the driving simulator software at a sampling rate of 50 Hz, including the driver input from the steering wheel and the pedals, and the status change of the automation system. Three cameras from different angles were installed in both cabins to record the participants' facial expressions, full body movement, and feet movement, respectively.

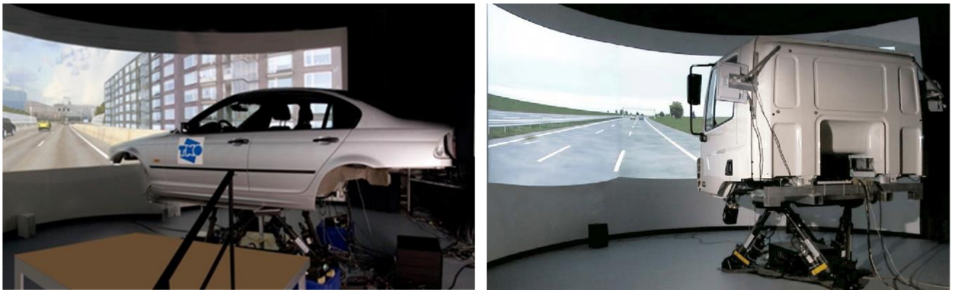

Figure 5.1: Configurations of the TNO moving-base driving simulator and cylindrical projection screen in two experiments. Left: The car platooning experiment with a BMW passenger car mock-up; Right: The same set-up with a DAF truck mock-up.

5.2.3 Automated platooning system

In the study, an automated platooning system was simulated that allowed a vehicle to follow its predecessor at a relatively short following distance, controlling both the longitudinal and lateral motion. The system was designed to operate on public motorways (i.e. without using dedicated lanes), initially limited to platoons of two vehicles. The first vehicle was intended to be driven by a human operator (but was controlled by the simulator scripts in our studies), and the second vehicle was controlled by the automated system once engaged. The automated platooning system was modelled as a combination of Cooperative Adaptive Cruise Control (CACC) and a Lane Keeping System (LKS). The driver could push a button (normally used for cruise control) on the left side of the steering wheel to switch the system on and off. To be able to switch the system on, the driver had to drive in an activation zone behind the lead vehicle. Once activated, the driver did not need to monitor or supervise the system, thus simulating SAE L3/4 automated driving.

Upon approaching the end of the automation zone, the system would issue a take-over request (TOR) by displaying a text message (in Dutch: "*Neem de controle over*", in English: "*Take over control*") on an orange background on the visual interface presenting the automation status, accompanied with an alert sound. The driver then had to push the button again to deactivate the automated system and take over both longitudinal and lateral control.

5.2.4 Experimental design and test procedures

The experimental design and procedures were identical for both experiments. Prior to driving, the participants read an introduction to the experiment and the automated platooning system, and filled in a questionnaire on their demographics and driving experience. Subsequently, a training session was conducted to familiarize the participants with the driving simulator and with the platooning system. The participants performed the coupling and decoupling procedures at least three times, until they felt familiar and comfortable with the system. After the training, each participant performed one manual driving trial and seven platooning trials. In each trial, the participants were instructed to drive on the right-hand lane of a two-lane motorway, behind a lead vehicle that was driving with an average speed of 100 km/h in the car platoon and 80 km/h in the truck platoon. The participants were instructed to follow this lead vehicle and not to change lanes. There were no entries or exits on the route the participants drove. Slight curves and moderate surrounding traffic were simulated throughout the scenario.

The manual driving trial was always performed first and served as the baseline condition, in which the participants followed the lead vehicle without assistance from automation systems. In the platooning trials, the participants were instructed to drive into the activation zone and switch on the platooning system shortly after the scenario began (approximately 10 – 20 s). In each trial a different experimental condition was implemented by manipulating three independent variables, namely non-driving tasks, the time gap to the lead vehicle in the platoon (0.8 s vs. 0.3 s), and whether a braking event occurred after the participant took over control. The order of the conditions was counterbalanced. This paper only discusses the five trials in which the time gap was set to 0.8 s during automated driving (i.e., the minimum allowed time gap defined in ISO 15622, which is considered to be the accepted distance for testing the first truck platooning concepts).

In each platooning trial, one of three non-driving task conditions was implemented during the automated driving phase. In the *Monitoring* condition, the participants were instructed to constantly monitor the surroundings, so hands-off, feet-off, and eyes on the road; in the *Tablet* condition, the participants were provided with a tablet PC and were asked to use this, so hands-off, feet-off, and eyes off the road, but they were allowed to scan the outside world if they wanted; in *Eyes-closed* condition, the participants were not allowed to open their eyes, so hands-off, feet-off, and eyes off the road. These conditions manipulated participants' visual attention and represented three activities likely to be performed by the driver in future automated vehicles. After four minutes in the *Monitoring* condition, or eight minutes in the *Tablet* and *Eyes-closed* conditions, a TOR was issued and the participants were instructed to take over control by pressing the button whenever they felt ready to do so without time restrictions. The automation duration was shorter for the *Monitoring* condition to increase the possibility that drivers were still paying attention and were alert, and longer for the other two conditions increase the chance of the driver being out-of-the loop. After the transition, the participants continued with manual driving for approximately 90 s until the end of the scenario.

In three trials, no critical events were implemented after the transition to investigate the driver's performance to stabilize the vehicle and regulate the following distance in normal, uneventful situations. In the other two trials (in *Monitoring* and *Tablet* conditions, respectively), a lead vehicle brake event was implemented shortly after the control transition to explore whether the participants possessed sufficient readiness to cope with more complex situations. Three seconds after the participant pressed the button to deactivate the system, the lead vehicle started braking at a deceleration rate of 5 m/s^2 for two seconds. No forward collision warnings or brake assist systems were available, and participants had to respond in time to avoid a potential collision. An overview of all experimental conditions is provided in Table 5.1.

Table 5.1: Overview of experimental conditions analysed in this study

Condition	Task during AD	Post-transition brake event	Duration
0 (MD)	-	-	6.5 min MD
1 (AD)	Monitoring	N	4 min AD + 1.5 min MD
2 (AD)	Tablet	N	8 min AD + 1.5 min MD
3 (AD)	Eyes-closed	N	8 min AD + 1.5 min MD
4 (AD)	Monitoring	Y	4 min AD + 1.5 min MD
5 (AD)	Tablet	Y	8 min AD + 1.5 min MD

Note. AD = Automated Driving; MD = Manual Driving.

5.2.5 Dependent measures

In this study, measures regarding take-over response times and take-over quality were assessed and compared between the two experiments, which are introduced in details below.

5.2.5.1 Response times to a take-over request

The total take-over response time was measured from the onset of the TOR until the participant pressed the button to deactivate the platooning system. As in Zhang, Wilschut et al., (2019), the total response time was further divided into perception response time and hand movement response time to analyse the take-over process at a fine-grained level. Perception response time was the response time measured from the onset of the TOR until the participant started to move his/her hands towards the steering wheel, which indicated the time elapsed between perceiving the TOR and understanding the necessity to take over control and starting to take action. Movement response time was the remaining response time measured until the participant pressed the button, indicating the time it took to complete the physical response and to establish motor readiness. The start of the participants' hand movement, the participants' body postures at the moment of the TOR onset, and the activities performed during the take-over process were manually annotated from video recordings to explore underlying factors influencing their take-over response times. In addition, we analysed the gas pedal response time measured from the moment when the participant pressed the button to disengage the automation until the moment when the first input on the gas pedal was made to inspect how the driver regulated speed after overruling the system. All response time measures described in this section were only analysed for experimental trials without brake events.

5.2.5.2 Take-over quality

5.2.5.2.1 Post-transition manual driving performance

For the experimental trials without brake events, we analysed the standard deviation of lateral position (SDLP), the mean and standard deviation of longitudinal speed, and the mean time headway (THW) to assess drivers' performance to stabilize the vehicle in its lane and to maintain a safe following distance after taking over manual control. The SDLP was calculated based on the high-pass filtered (at 0.1 Hz) lateral position signal (to remove effects caused by the driver's low-frequent shifting of lane position, in line with Engström and Markkula, 2007). Merat, Jamson, Lai, Daly, and Carsten (2014) suggested that drivers may need 40-50 s to stabilize the vehicle after the control transition. In our study, the performance measures were analysed in time windows of 10 s for 60 s after the control transition. In addition, we explored carry-over effects of platooning by comparing drivers' mean THW and SDLP after the control transition to their performance in the baseline manual driving condition. To enable a fair comparison, we chose a one-minute timeslot in the baseline condition, starting at five minutes after the start of the scenario, divided in six time windows of 10 s.

5.2.5.2.2 Post-transition brake response

For the experimental trials with brake events after the control transition, participants' responses to the braking lead vehicle were analysed. Relevant measures were brake response time, the maximum longitudinal deceleration, and the minimum time-to-collision (TTC) with the lead vehicle. The brake response time was defined as the time interval between the onset of the braking light of the lead vehicle and the moment at which the participant started pressing the brake pedal.

5.2.6 Data analysis

Several experimental trials were not available for analysis due to missing or incomplete video recordings or driving performance data. An overview of data availability is provided in Table 5.2. Mixed factorial analysis of variance (ANOVA) was conducted to examine the effects of *driver group* (between-subject factor) and *task* (within-subject factor) on each dependent variable related to take-over responses and brake responses. To assess post-transition manual driving performance as a function of time, *time* was included as an additional within-subject factor in the mixed factorial ANOVA. If Mauchly's tests indicated that the assumption of sphericity had been violated, degrees of freedom were corrected using Greenhouse-Geisser estimates. Post-hoc pairwise comparisons were performed using the Bonferroni correction.

Table 5.2: Overview of data availability for analysis. BE = Brake Event.

	Test conditions	**Trials with available video recordings**	**Trials with available driving performance data**	**Total number of trials**
Car	Monitoring (w/o BE)	17	17	18
	Tablet (w/o BE)	16	15	18
	Eyes-closed (w/o BE)	17	15	18
	Monitoring (BE)	-	13	18
	Tablet (BE)	-	13	18
	Manual driving	-	17	18
Truck	Monitoring (w/o BE)	18	19	22
	Tablet (w/o BE)	17	19	22
	Eyes-closed (w/o BE)	18	20	22
	Monitoring (BE)	-	20	22
	Tablet (BE)	-	17	22
	Manual driving	-	22	22

Because subjects with any missing value would be excluded from repeated measures ANOVA, we first imputed missing values using the expectation maximization (EM) method (Dempster, Laird, & Rubin, 1977) to make sure we were able to at least use all available data. All statistical analyses were performed using IBM SPSS 24; with a significance level of 0.05. Descriptive results were reported based on the original datasets without imputation.

5.3 Results

5.3.1 Take-over response times

Combining all task conditions, car drivers took over control on average 3.78 s (SD = 1.79 s) after the TOR onset, ranging from 1.6 s to 9.56 s. For truck drivers, the average take-over response time was 4.45 s (SD = 2.18 s), ranging from 1.75 s to 11.77 s. In both groups, 95 % of the drivers could take over within 8.5 s. Descriptive statistics of car and truck drivers' perception-movement times during the take-over process (total response time, perception response time, and movement response time), and the response time to press the acceleration pedal after automation deactivation (acceleration response time) were measured in three task conditions, as listed in Table 5.3, and visualised in Figure 5.2 and Figure 5.3. Results of 2 (*driver group*) ×3 (*task*) two-way mixed factorial ANOVAs are presented in Table 5.4.

There was a significant main effect of *task* on the total response time, while the main effect of *driver group* was not significant. Total response times were significantly shorter in the *Monitoring* condition compared to the *Table*t condition and the *Eyes-closed* condition (both at p <.001). Interaction between the effects of *task* and *driver group* was only marginally significant, with car drivers having the tendency to respond faster than the truck drivers in the *Tablet* condition.

A significant main effect of *task* was found on the perception response time, while the main effect of *driver group*, and the interaction effect were not significant. Post-hoc tests revealed significantly longer perception response times in the *Eyes-closed* condition compared to the *Monitoring* condition (p <.001) and *Tablet* condition (p =.001). With respect to the movement response time, significant main effects of *task* and *driver group*, and a significant interaction were found. Post-hoc tests showed significantly higher movement response times of truck drivers than car drivers in the *Eyes-closed* condition (p =.008), and a similar trend in the *Tablet* condition (p =.057). When comparing between task conditions, both driver groups showed significantly higher movement response times in the *Tablet* condition compared to the *Monitoring* condition (p <.001 for both driver groups) and the *Eyes-closed* condition (p <.001 for car drivers, p =.006 for truck drivers). Higher movement response times in the *Eyes-closed* condition compared to *Monitoring* condition was only significant for truck drivers (p =.018). In addition, we performed pairwise comparisons to compare the perception response time and the movement response time in all conditions, and found that for both driver groups, the movement response time was significantly larger than the perception response time in the *Monitoring* and *Tablet* conditions (all at p <.001). The difference between the perception response time and the movement response time was not statistically significant in *Eyes-closed* condition.

Both *driver group* and *task* showed significant main effects on the gas pedal response time. The interaction between the main effects was not significant. After the control transition, truck drivers pressed the gas pedal significantly later than the car drivers. Pairwise comparisons further revealed a significantly lower gas response time in the *Monitoring* condition than the *Tablet* condition (p = .014). No significant differences in gas response time were found between other task conditions.

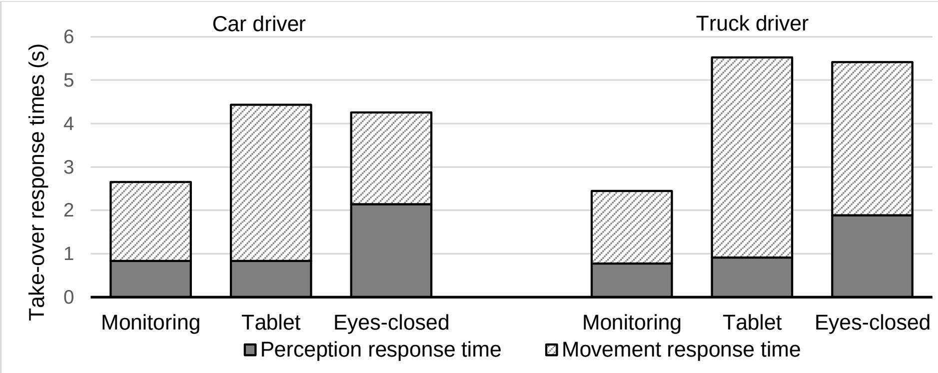

Figure 5.2: Take-over response times of car drivers and truck drivers measured in three non-driving task conditions. The bars show the means of perception response times and movement response times; they add up to the total take-over response times.

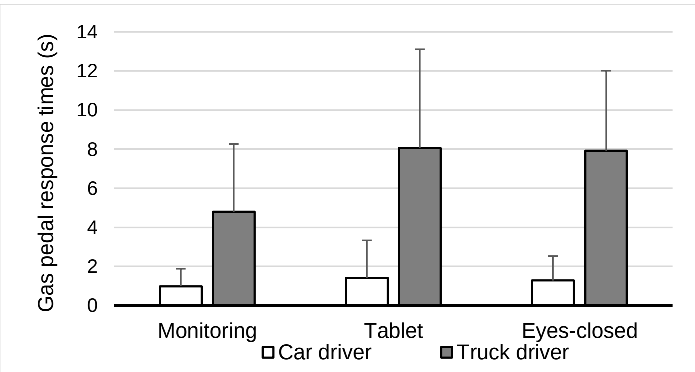

Figure 5.3: Car drivers' and truck drivers' mean response times to press the acceleration pedal after automation deactivation in three non-driving task conditions. The error bars represent the standard deviations.

Table 5.3: Descriptive statistics of the four take-over response time measures.

Measure	Task	Car			Truck		
		Mean (SD)	Min.	Max.	Mean (SD)	Min.	Max.
Total response time (s)	Monitoring	2.66 (0.96)	1.60	4.55	2.45 (0.53)	1.75	3.80
	Tablet	4.43 (1.49)	2.15	8.32	5.53 (1.39)	3.62	8.54
	Eyes-Closed	4.26 (2.13)	1.96	9.56	5.42 (2.44)	2.19	11.31
Perception response time (s)	Monitoring	0.84 (0.35)	0.55	1.96	0.78 (0.14)	0.43	1.10
	Tablet	0.84 (0.28)	0.43	1.53	0.91 (0.35)	0.17	1.77
	Eyes-Closed	2.14 (2.08)	0.58	8.39	1.89 (1.66)	0.80	7.73
Movement response time (s)	Monitoring	1.82 (0.84)	0.82	3.87	1.67 (0.49)	0.95	2.97
	Tablet	3.60 (1.43)	1.17	7.07	4.61 (1.40)	2.75	7.74
	Eyes-Closed	2.11 (0.81)	1.05	3.99	3.53 (1.90)	1.19	8.31
Gas pedal response time (s)	Monitoring	0.99 (0.89)	0.05	3.45	4.80 (3.47)	0.05	11.90
	Tablet	1.42 (1.91)	0.04	3.89	8.06 (5.05)	0.50	21.70
	Eyes-Closed	1.28 (1.25)	0.05	5.18	7.92 (4.09)	0.05	14.33

Table 5.4: Results of mixed ANOVAs for the four take-over response time measures.

Measure	Factor	*F*	*df*	*p*	Partial η^2
Total response time	driver group	2.51	1, 38	.122	.06
	task	46.28	1.65, 62.66	**<.001**	.55
	driver group * task	3.16	1.65, 62.66	.059	.08
Perception response time	driver group	.05	1, 38	.822	.00
	task	16.32	1.06, 40.25	**<.001**	.30
	driver group * task	.12	1.06, 40.25	.744	.00
Movement response time	driver group	5.60	1, 38	**.023**	.13
	task	51.65	2, 76	**<.001**	.58
	driver group * task	5.05	2, 76	**.009**	.12
Gas pedal response times	driver group	46.29	1, 38	**<.001**	.55
	task	3.80	2, 76	**.027**	.09
	driver group * task	1.61	2, 76	.206	.04

p <.05 is indicated in boldface

5.3.2 Post-transition manual driving performance

Car and truck drivers' post-transition manual driving performance in terms of SDLP, mean and standard deviation of longitudinal speed, and mean THW in three task conditions were depicted in Figure 5.4, Figure 5.5, Figure 5.6, and Figure 5.7. Table 5.5 showed the results of the 2 (*driver group*) × 3 (*task*) × 6 (*time*) three-way mixed factorial ANOVAs conducted for each performance measure.

First, we examined the effects of the three factors on drivers' lateral vehicle motion control performance (SDLP). Results indicated a significant main effect of *time*, and significant two-way interactions between each of the two factors. The effect of *time* was only significant for truck drivers in the *Tablet* condition (p <.001), in which truck drivers' SDLP significantly decreased within 10-20 s after the transition, and remained relatively stable in the remaining timeslots. When comparing between task conditions, truck drivers' SDLP in the *Tablet* condition was significantly higher than the *Monitoring* condition, but only for the first 10 s after the transition (p = .010). Significant differences between driver groups (p = .003) were only found in the *Tablet* condition, in which car drivers in general drove with lower SDLP compared to truck drivers. The post-transition SDLP was then compared to that measured in the baseline manual driving condition. For truck drivers, post-transition SDLP in the *Tablet* condition was marginally significantly higher than the baseline SDLP, but only for the first 10 s after transition (p = .06). No significant differences were found in the other two conditions. For car drivers, no significant differences were not observed in any task condition, for any timeslot.

Next, we assessed car and truck drivers' performance with respect to longitudinal speed. There were significant main effects of *driver group* and *time* on mean speed, and a significant two-way interaction between these two factors. In addition to car drivers' higher mean speed than truck drivers (which was a direct result of the experimental condition), we found that truck drivers' speed significantly decreased in the first 20 s after the transition, and then gradually increased in the successive timeslots, while car drivers' speed increased in the first 20 s after the transition, then remained relatively stable in the remaining timeslots. When examining the effects of the three factors on variation in longitudinal speed (SD SPD), we found significant main effects of *driver group* and *time*, and a statistically significant three-way interaction between *driver group*, *task*, and *time*. When comparing between driver groups, car drivers showed a significantly larger variation in speed than truck drivers in all task conditions, in all timeslots (all at p <.001). The effect of *task* was significant for truck drivers only in the first 10 s after the transition, in which the SD SPD was lower in the *Monitoring* condition compared to the other two task conditions ($p < .010$). Systematic effects of task were not observed for car drivers. The effect of *time* was only significant for truck drivers (p <.001). In each task condition, truck drivers' variation in speed significantly reduced in the first 20 s after the transition, and remained stable in the remaining timeslots.

Another mixed ANOVA was conducted to examine the effects of the three factors on the mean THW after the control transition. There were significant main effects of *driver group* and *time*, and a significant three-way interaction between *driver group*, *task*, and *time*. In all task conditions, car drivers' mean THW significantly increased only in the first 20 s after the transition. Truck drivers' mean THW continuously increased within the observation window in the *Tablet* and *Eyes-closed* conditions. In the *Monitoring* condition, truck drivers' mean THW only increased in the first 50 s after the transition. When comparing between driver groups, truck drivers' mean THW was significantly lower than car drivers in the first 10 s then overpassed that of car drivers from 20-30 s after the transition, in all task conditions. An exception was that 50 - 60 s after the transition in the *Monitoring* condition, the two driver groups did not show significant differences in THW. The effect of *task* was only significant for truck drivers (p = .004): from 10 s after the transition, truck drivers' THW was significantly lower in the *Monitoring* condition compared to the other two task conditions.

In addition, we assessed car and truck drivers' THW in the baseline (manual) driving condition. Truck drivers' post-transition THW was significantly lower compared to their baseline THW in all timeslots, in all conditions. For car drivers, a significantly lower post-transition THW than the baseline THW was only found in the first 30 s after the transition in the *Monitoring* condition. In the other two task conditions, a significantly lower post-transition THW compared to the baseline THW was found in the first 10 s after the transition, and at the end of the observation window (50 – 60 s).

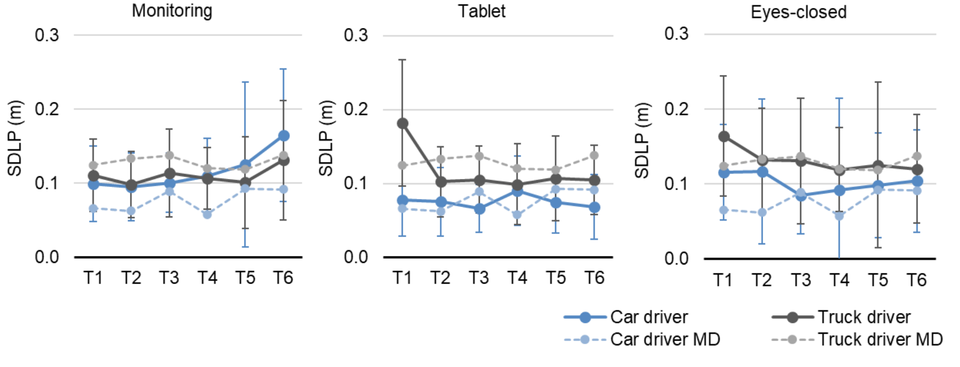

Figure 5.4: Car drivers' and truck drivers' mean standard deviation of lateral position (SDLP) for the first 6×10 = 60 s after the control transition measured in three task conditions, and between 5 min and 6 min after the scenario start in the baseline manual driving condition (MD, dashed lines). The error bars represent the standard deviations.

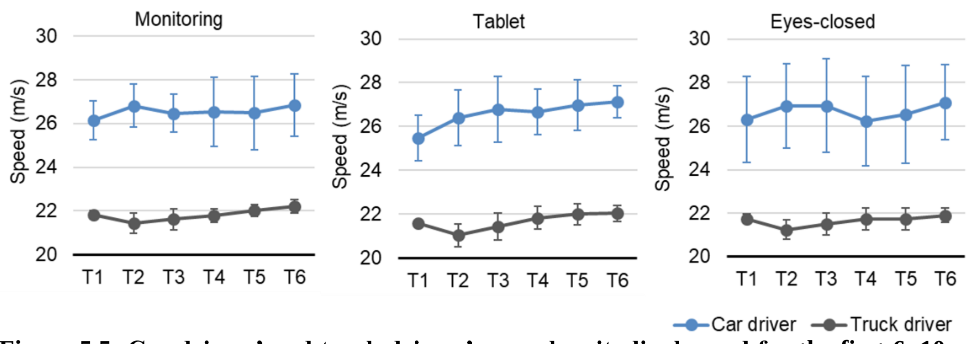

Figure 5.5: Car drivers' and truck drivers' mean longitudinal speed for the first 6×10 = 60 s after the control transition measured in three task conditions. The error bars represent the standard deviations.

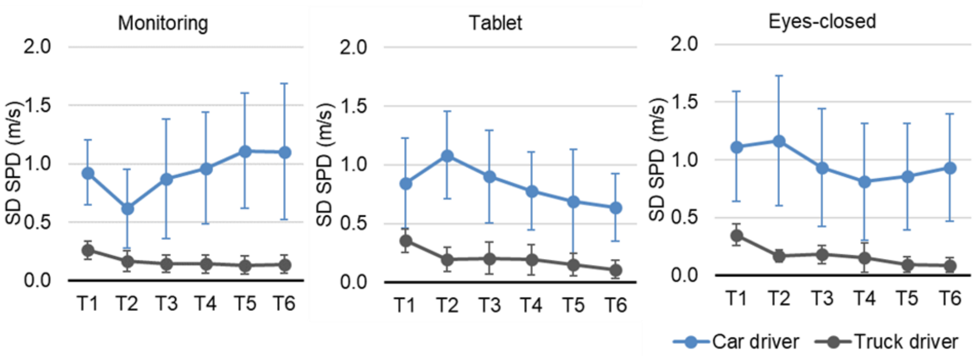

Figure 5.6: Car drivers' and truck drivers' mean standard deviation of longitudinal speed for the first 6×10 = 60 s after the control transition measured in three task conditions. The error bars represent the standard deviations.

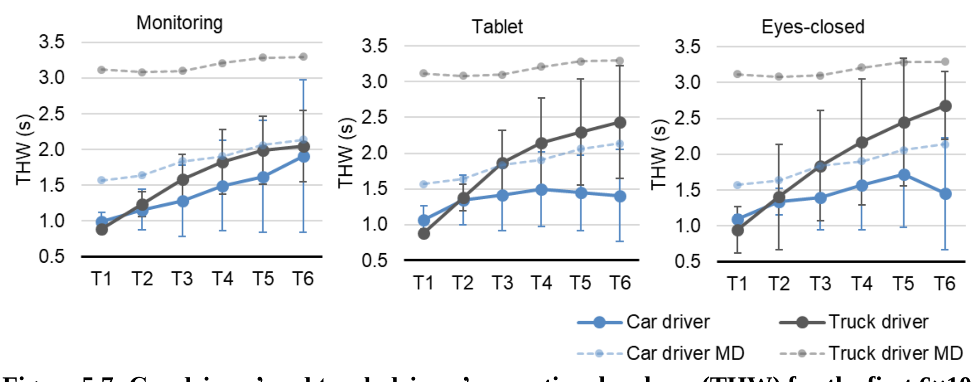

Figure 5.7: Car drivers' and truck drivers' mean time headway (THW) for the first 6×10 = 60 s after the control transition measured in three task conditions (solid lines), and between 5 min and 6 min after the scenario start in the baseline manual driving condition (MD, dashed lines). The error bars represent the standard deviations.

Table 5.5: Results of mixed ANOVAs for the post-transition manual driving performance measures.

Measure	Factor	*F*	*df*	*p*	*Partial* η^2
SDLP	driver group	3.82	1, 38	.058	.09
	task	2.86	2, 76	.063	.07
	time	4.62	2.99, 113.53	**.001**	.11
	driver group * task	4.85	2, 76	**.010**	.11
	driver group * time	3.63	2.99, 113.53	**.015**	.09
	task * time	3.18	6.43, 244.48	**.004**	.08
	driver group * task * time	1.03	6.43, 244.48	.409	.03
Speed	driver group	1000.31	1, 38	**<.001**	.96
	task	.04	1.37, 51.85	.912	.00
	time	11.08	3.41, 129.52	**<.001**	.23
	driver group * task	.30	1.37, 51.85	.654	.01
	driver group * time	10.20	3.41, 129.52	**<.001**	.21
	task * time	1.94	5.81, 220.62	.077	.05
	driver group * task * time	1.06	5.81, 220.62	.387	.03
SD SPD	driver group	327.90	1, 38	**<.001**	.90
	task	1.85	2, 76	.165	.05
	time	4.16	3.47, 131.87	**.005**	.10
	driver group * task	3.47	2, 76	**.036**	.08
	driver group * time	1.21	3.47, 131.87	.309	.03
	task * time	4.38	6.59, 250.27	**<.001**	.10
	driver group * task * time	3.24	6.59, 250.27	**.003**	.08
THW	driver group	13.41	1, 38	**.001**	.26
	task	1.39	2, 76	.254	.04
	time	91.35	1.42, 54.29	**<.001**	.71
	driver group * task	2.40	2, 76	.098	.60
	driver group * time	20.94	1.42, 54.29	**<.001**	.36
	task * time	1.48	3.89, 147.84	.214	.04
	driver group * task * time	5.32	3.89, 147.84	**.001**	.12

p <.05 is indicated in boldface.

5.3.3 Response in post-transition brake events

Car drivers' and truck drivers' brake response times, maximum deceleration rate, and minimum TTC in the post-transition brake event were depicted in Figure 5.8. The descriptive statistics are presented in Table 5.6. In both experiments, all participants successfully avoided a collision with the decelerating front vehicle by braking. Three 2 × 2 mixed ANOVAs were performed to test the effects of *driver group* and *task* (*Monitoring* vs. *Tablet*) on each performance measure. The results are presented in Table 5.7.

There were significant main effects of both *driver group* and *task* on brake response times (BRT), but no significant interaction between the main effects. In both task conditions, truck drivers responded significantly faster than car drivers (both at p <.001). A significantly shorter BRT in the Monitoring condition compared to the *Tablet* condition was only found for car drivers (p = .023). When examining maximum deceleration during the brake response, we only found a significant main effect of *driver group*. Truck drivers braked less aggressively compared to car drivers in both *Monitoring* (p <.001) and *Tablet* conditions (p = .003). In terms of minimum TTC, both driver groups displayed similar performance in the two task conditions.

The results indicated no significant main effects of *driver group* or *task*, nor significant interaction between the two factors.

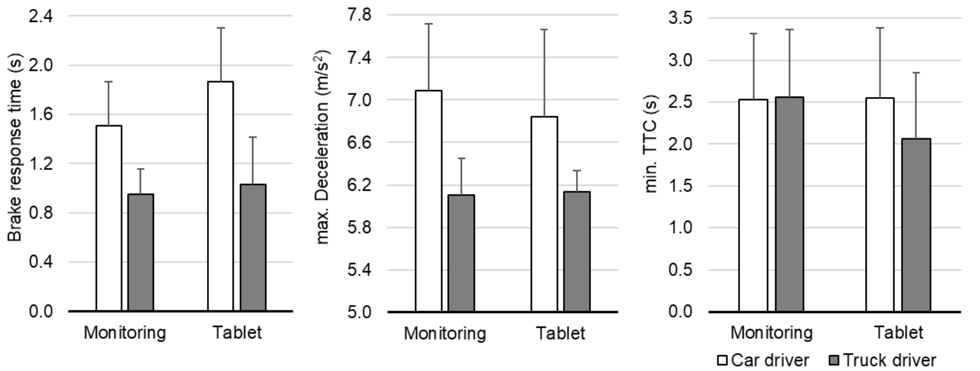

Figure 5.8: Brake response measures compared between truck drives and car drivers in three task conditions. Left: means brake response times (BRT); middle: mean maximum deceleration during the brake response; right: mean minimum time to collision (TTC) during the brake response. The error bars represent the standard deviations.

Table 5.6: Means, standard deviations and confidence intervals of the brake response times, maximum deceleration rate, and minimum TTC in the post-transition brake event.

Measure	Task	Car			Truck		
		Mean (SD)	Min.	Max.	Mean (SD)	Min.	Max.
BRT	Monitoring	1.15 (0.36)	0.75	2.40	0.95 (0.20)	0.60	4.15
	Tablet	1.86 (0.44)	1.04	2.41	1.03 (0.38)	0.05	1.60
max. Dec.	Monitoring	7.09 (0.63)	6.33	8.25	6.10 (0.35)	4.72	6.22
	Tablet	6.84 (0.83)	5.42	8.28	6.13 (0.20)	5.42	6.22
min. TTC	Monitoring	2.52 (0.79)	1.26	3.99	2.56 (0.81)	1.53	4.15
	Tablet	2.55 (0.83)	1.42	3.89	2.07 (0.78)	1.13	3.80

Table 5.7: Results of mixed ANOVAs for the post-transition brake response performance measures.

Measure	Factor	*F*	*df*	*p*	*Partial* η^2
BRT	driver group	51.50	1, 38	**<.001**	.58
	task condition	8.64	1, 38	**.006**	.19
	driver group * task condition	1.77	1, 38	.192	.04
max. Dec.	driver group	33.85	1, 38	**<.001**	.47
	task condition	1.09	1, 38	.302	.03
	driver group * task condition	1.55	1, 38	.220	.04
min. TTC	driver group	.81	1, 38	.374	.02
	task condition	2.34	1, 38	.134	.06
	driver group * task condition	2.61	1, 38	.114	.06

p <.05 is indicated in boldface.

5.4 Discussion

In this study, we took the initiative to compare professional truck drivers' and passenger car drivers' take-over performance when leaving a highly automated platoon measured in two comparable driving simulator experiments. The results outlined similarities and differences between two driver groups regarding take-over response times, post-transition manual driving performance, and post-transition brake. Note that all results should be seen in the light of the fact that truck drivers drove at a lower speed (80 km/h) than car drivers (100 km/h). The gap distance in the truck platoon was also 4.5 m shorter than in the truck platoon. These may cause differences in driver's risk perception, and additionally contribute to the behavioural differences between driver groups. Also to be noted is that the findings were based on comparisons of two independent experiments, which may be another source of differences between driver groups. The main findings are discussed in turn below.

5.4.1 Take-over response times

First of all, task conditions showed similar effects for professional truck drivers' and passenger car drivers' on take-over response times. For both truck and passenger car drivers, monitoring the road lead to lower take-over time compared to using a handheld tablet or relaxing with eyes closed. For both driver groups, the movement response time was the dominant response time component in the *Monitoring* and the *Tablet* conditions, while in the *Eyes-closed* condition, the perception time increased, leading to similar perception times and movement times.

When comparing between the driver groups, professional truck drivers and passenger car drivers did not depict distinct differences in total take-over response times, except for the *Tablet* condition in which car drivers took over control significantly faster than truck drivers. The analysis of perception-movement response times revealed the main cause to be truck drivers' slower hand movement response. When examining the video recordings for underlying reasons, we discovered that several truck drivers, but none of the car drivers, had to put on or off their glasses in order to change focus from the tablet PC back to the road, and took longer time than others to pause the undergoing task and shut down the tablet screen before putting it aside. These findings may be the result of truck drivers' higher mean age and age-related eye conditions such as presbyopia (for relation between ageing and presbyopia, see Heys, Cram, & Truscott, 2004), and potentially less experience with mobile technological devices (Vaportzis, Giatsi Clausen, & Gow 2017). In our study we did not check for experience with tablet use. Another possible explanation for truck drivers' longer movement time could be a longer spatial distance to put away the tablet PC associated with heavy trucks' larger cabin size. The difference in the cabin layout may also account for truck drivers' higher movement response in the Eyes-closed condition. Video recordings revealed that a number of truck drivers deliberately adjusted the seat while taking over control from the resting posture, which was not observed among car drivers (only one slightly adjusted the seat). Notably, our findings are not consistent with the speculation by Lotz et al., (2019) that professional truck drivers take over faster than passenger car drivers. In their study, that also involved a tablet task, the tablet PC was mounted on the central console rather than holding it in the hands, which did not allow to capture the large effect of movement response on truck drivers (having to put away the tablet). In addition, compared to critical transitions in Lotz et al., (2019), take-over times measured in self-regulated transitions reflect drivers' motivation more than their capability or biological limitations (Zhang, De Winter et al., 2019). Truck drivers in the current study could behave differently in emergency situations and take over before being physically comfortable.

In addition to the regular take-over response times, we examined the response times to press the gas pedal after the control transition, and found quite some differences between driver groups. While car drivers pressed the gas pedal on average 1 – 1.5 s after disengaging the system, professional truck drivers pressed the pedal approximately 4 – 7 s later. We additionally examined the corresponding THWs at the moment of the acceleration initiation, but did not found significant differences (on average 0.91 s for car drivers and 1.04 s for truck drivers). It might be that both driver groups share a similar THW threshold to initiate car-following manoeuvres after platooning. Truck drivers appeared to be aware of the lower coasting deceleration rate of their vehicles and deliberately delayed the initial input on the gas pedal to increase the THW to this threshold. Another finding worth noticing is that drivers of both groups pressed the gas pedal significantly later in the *Tablet* condition compared to the *Monitoring* condition. This could be that drivers' sensory adaptation to the small gap during platooning was stronger while monitoring the driving environment due to sustained visual stimulation (Skottke et al., 2014; Wark, Lundstrom, & Fairhall, 2007). That is, after keeping the eye on the preceding vehicle for a prolonged time during platooning, the driver might not feel the gap as small as just switching the gaze back to the road, and felt it less risky to start manual car-following at a smaller distance.

5.4.2 Post-transition manual driving performance

Differences between car and truck drivers' post-transition manual driving performance are mainly exhibited in longitudinal vehicle control. Within our observation, truck drivers drove at a more steady speed and in general with a larger THW compared to car drivers. This is in line with previous research (e.g., Aghabayk et al., 2011; Aghabayk et al., 2012; Rosenbloom, 2011) that reported a significant larger THW in the truck-following-truck case than the car-following-car cases, and truck drivers' smoother and more cautious car-following behavior. When examining the change of speed as a function of time, both driver groups showed the pattern of first decreasing and then increasing the mean speed after the transition in order to increase THW. A similar phenomenon was found in a recently study by Varotto et al., (2020) that investigated passenger car drivers' behavioral adaptation after using a full-range ACC. In this study, car drivers' mean speed reduced very shortly after the transition (and therefore was not depicted in Figure 5.5 due to the large observation window), then rapidly increased to approximately 27 m/s in the following 10-20 s. Truck drivers' mean speed reduced by approximately 1m/s between the first two timeslots, then gradually increased to the previous speed level 40 – 60 s after the transition. This difference in speed regulation corresponds to our finding that truck drivers started pressing the gas pedal at a much later stage than car drivers, and explains the difference in the THW regulation. Car drivers' THW only increased within the first 20 – 30 s after the transition, while truck drivers' THW continuously increased within the observation window and overpassed that of car drivers from 20 s after the transition.

When examining the carry-over effects of platooning in longitudinal control, we found that truck drivers' post-transition THW continued to approach the baseline manual driving THW, but still didn't reach a comparable level at the end of the observation. Truck drivers' THW in the *Monitoring* condition increased more slowly after take-over, and was in general shorter compared to the other two conditions. This supports our speculation that monitoring the preceding vehicle during platooning may increase the carry-over effects, particularly for truck drivers. For car drivers, significant differences between the post-transition THW and the baseline manual driving THW started to diminish 20 – 30 s after the transition. However, we speculate that the carry-over effects may last longer for car drivers, seen from the smaller mean THW compared to the baseline and several drivers' very small THW (< 0.8 s) in the following timeslots. Empirical evidence by Skottke et al., (2014) suggested that carry-over effects on

THW could last for 6 min after the control transition. Unfortunately, the short observation window in our study did not allow to investigate the development of the carry-over effect in further manual driving periods. It also has to be noted that we compared the THW after a take-over with the preferred headway from the manual drive that participants made. However, these mean headways (3.18 s for truck drivers and 1.86 s for car drivers) were the headways chosen in low-volume traffic conditions, which can be considerably larger than that observed under high-volume traffic conditions (typically 1 – 2 s, Ayres, Li, Schleuning, & Young, 2001). Cautions should be exercised when generalizing the outcomes to more complex driving environments.

With respect to lateral control performance, only truck drivers depicted increased SDLP immediately (the first 10 s) after the transition in the *Tablet* condition. This finding suggested a larger impact of platooning on truck drivers' lateral control performance compared to that or car drivers, especially after being engaged in visually and motorically demanded non-driving tasks.

In addition, we suggest that compared to car drivers, truck drivers may require more time to stabilize their control of the vehicle after the transition to manual, as the effect of *time* was significant for truck drivers in all performance measures. In particular, the variations in truck drivers' lateral and longitudinal vehicle control systematically reduced and came to a stable status approximately 30 - 50 s after the transition. For car drivers such patterns were not clearly observed. This could be a result of the difference in simulated vehicle dynamics.

5.4.3 Post-transition brake response

In both experiments, all drivers braked in time in response to the decelerating preceding vehicle immediately after the transition, and no collision occurred. This indicated that both car drivers and truck drivers were indeed ready for moderately critical driving situation when taking over control at a comfortable pace. Significant differences between driver groups were found regarding brake response time and maximum deceleration. Car and truck drivers' minimum TTC did not differ, possibly due to the interplay of truck drivers' faster brake response but less aggressive deceleration compared to car drivers. Differences among task conditions were only found for car drivers, who braked more slowly after using the tablet PC compared to monitoring the driving situation. Truck drivers' more robust and significantly better braking response corresponds to their higher level of training and expertise than average car drivers. In addition, given the similar THW when the brake event occurred (mean THW was 0.90 s for car drivers and 0.86 s for truck drivers), truck drivers may perceive the situation to be more risky than car drivers, knowing heavy vehicle's lower braking capability.

5.5 Conclusion

This paper investigated differences in take-over performance between professional truck drivers and car drivers when leaving an automated platoon. During the take-over process, differences between two driver groups mainly lay in car drivers' shorter movement time to resume motor readiness for manual driving, possibly associated with their lower mean age and a smaller cabin size. After disengaging the system, truck drivers showed a smoother and more cautious driving style, suggested by their later input on the gas pedal (to reduce speed and increase THW), slower and more steadily increase in speed, larger THW, and faster but less aggressive response in the brake event. Furthermore, carry-over effects of platooning were suggested for both driver groups in car-following performance, which appeared more pronounced for truck drivers after monitoring the preceding vehicle due to sensory adaptation to the small gaps. Truck drivers also showed impaired lane keeping performance after using a handheld tablet PC, which was recovered rapidly after the control transition. A transition zone between a dedicated automation zone and public roads, or an HMI that reminds drivers of their following distances after platoon driving would be potential measures to ensure safe manual driving immediately after the transition.

In the end, we provide implications for future research. As mentioned above, the driving environment in the current study was relatively simple with low traffic volumes, and drivers may behave differently under heavy-volume traffic conditions. Varotto et al., (2020) reported a larger acceleration and a larger increase in speed when the driver overruled the ACC system at higher traffic densities, which could also be the case after taking over control from CACC systems for platooning. In future research, a more complex driving situation could be simulated to investigate the influence of traffic density and the behaviours of non-platoon road users on platoon drivers' take-over performance. In addition, the platooning durations of our experiment trials were less than 10 min, and only three task conditions were implemented. Future studies could incorporate longer platooning drives without critical events, and a large variation of task conditions to emulate natural platooning environment.

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6. The effect of see-through truck on driver monitoring patterns and responses to critical events in truck platooning

This chapter is based on Zhang, B., Wilschut, E. S., Willemsen, D. M. C., Alkim, T., & Martens, M. H. (2017). The effect of see-through truck on driver monitoring patterns and responses to critical events in truck platooning. In N. A. Stanton (Ed.), *Advances in human aspects of transportation* (pp. 842 -852). Cham: Springer.

6.1 Introduction

The technological progress in intelligent transportation systems (ITS) and communication technologies enables rapid development of automated vehicles. Some vehicles already have systems such as Traffic Jam Assist that work at low speeds, which can keep a distance to the vehicle in front (e.g., based on Adaptive Cruise Control) and take control of the lateral position of a car within its lane based on road markings (Lane Keeping Assist System). Drivers are thus relieved from dynamic control tasks in specific situations. There are systems available or under development that work on motorways at higher speeds as well. One example is cooperative platooning, which can be defined as a group of automated vehicles travel closely together for the benefits of energy saving, traffic flow efficiency and safety (Bergenhem, Shladover, Coelingh, Englund, & Tsugawa, 2012; Alam, Besselink, Turri, Mårtensson, & Johansson, 2015). In 2016, the Netherlands initiated a European Truck Platooning Challenge where partially automated trucks of various brands travelled in a platoon to the Netherlands from different European cities (e.g., DAF Trucks participated under the name of the 'EcoTwin' project), showing the possibility and readiness of trucking platooning to be implemented on public roads in the near future.

Despite the promising perspective, considerable efforts still have to be made to realize these high levels of automation where human intervention and supervision are rarely needed. The current commercially available systems are not yet able to cooperate with human drivers/supervisors at an optimal level (Martens & Van den Beukel, 2013), and the drivers are still required to be prepared to take over immediate manual control in case of system boundaries and failures. Maintaining sufficient situation awareness about the surrounding driving environment and system status therefore becomes safety critical. However, this can be challenging even for drivers who are constantly monitoring because this monotonous task can easily cause boredom and vigilance decrement, which can cause slow and inadequate responses (Körber, Schneider, Zimmermann, 2015). The situation is especially disadvantageous for the drivers in a truck platoon when the time headways to the lead truck have to be extremely low (between 0.2 and 0.3 s) in order to effectively save up fuel consumption by reducing air resistance (Bergenhem et al., 2012; Willemsen, Stuiver, & Hogema, 2015). On the one hand, the blocked and monotonous front view may increase difficulties for the platoon drivers to stay "in the loop", and anticipate upcoming traffic situations. Consequently, platoon drivers may not be able to anticipate critical situations until being notified by the system. In extreme cases where timely warning cannot be guaranteed, the drivers are forced to respond immediately and an unsafe situation is most likely to occur due to a lack of preparation. Although it is a highly exceptional situation and should in principle not occur, it is interesting to study how critical this will be and if additional measures may be helpful.

One additional measure may be to capture real-time video streams by a camera installed in the front of the vehicle, and broadcast the image to the following vehicle either through an in-vehicle device (Belyaev, Vinel, Egiazarian, Koucheryavy, 2013; Gomes, Vieira, & Ferreira, 2012; Olaverri-Monreal, Gomes, Fernandes, Vieira, & Ferreira, 2010; Patra, Arnanz, Calafate, Cano, & Manzoni, 2015) or on a large screen attached to the back of the lead vehicle such as implemented in Samsung Safety Truck (Samsung Newsroom, 2015). These see-through systems (STS) provide drivers with very intuitive traffic information and facilitate safety assessment during overtaking manoeuvres.

Seeing the potential benefits of implementing STS in truck platooning systems, we aimed to investigate whether providing platoon drivers with additional visual information of the forward traffic scene can influence their monitoring pattern and increase awareness of the upcoming situation. A driving simulator experiment was conducted in the present study to analyze driver gaze behaviour and responses to a sudden and time-critical event when following a see-through lead truck (i.e., with a screen at the rear part, inspired by the Samsung Safety Truck). A normal lead truck served as the control condition. Accordingly, the hypotheses were formulated as follows:

1. When driving behind a see-through truck, the forward scene becomes less monotonous and drivers will allocate more time monitoring the road, especially the see-through screen area.

2. More information about the situation by means of a see-through truck helps a driver to respond more quickly and less severely in case of an emergency situation.

6.2 Method

6.2.1 Participants

Twenty-two participants took part in the experiment. They all held a truck driver's license for at least 8 years and drove at least 10,000 km per year. On average participants were 47.4 years old, with a standard deviation of 11.5. Minimum age was 27 and maximum 64 years old. The group consisted of 20 male and 2 female drivers. The experiment was approved by the Ethical Committee for participant studies of TNO.

6.2.2 Apparatus

The experiment was carried out in a high fidelity moving base driving simulator consisting of a DAF truck mock-up mounted on a 6 DOF moving base. The road and traffic environment were projected on cylindrical screens around the vehicle with a horizontal viewing angle of 180° and two external rear view mirrors. Vehicle and situational parameters such as pedal positions, speed, steering wheel angle and button reaction time were recorded at a sampling rate of 50 Hz. Synchronously, driver eye movements were recorded using a SmartEye nonobtrusive remote eye tracker (SmartEye AB, Gothenburg, Sweden) at a sampling rate of 60 Hz.

6.2.3 Two-truck Platooning System

In this experiment, an automated two-truck platooning system was simulated that allows a truck to follow a lead vehicle at a relatively short following distance, controlling both the longitudinal and lateral motion of the vehicle. The first truck is intended to be driven by a human operator (but is controlled by the simulator in the experiment). Once engaged, the second truck is controlled by the automated system. The automated system was modelled as a combination of a Cooperative Adaptive Cruise Controller (CACC) and a Lane Keeping Assist System (LKA). The driver could push a button normally used for cruise control on the right side of the steering wheel to switch the automated system on/off. To be able to switch the system on, the driver had to drive in an 'activation zone' behind the lead truck at a distance close enough to hook on. After activating the system by pushing the 'on/off' button the system would take over both longitudinal and lateral control. To deactivate the automated system, the driver had to push the 'on/off' button again. The automated system would then transfer both longitudinal and lateral control back to the driver. A tablet display located at the right side of the dashboard indicated status change of the automated systems.

6.2.4 Experimental Design and Test Procedure

Participants drove in the right-hand lane (the slower lane) of a two-lane motorway behind a lead truck that was driving with an average speed of 80 km/h. The participants were instructed to follow this lead truck and not to change lanes. There were no entries or exits on the route the participants drove. Slight curves and surrounding traffic were included in the drive. All participants started with a training session to get familiar with the driving simulator and the automated driving system. During training they were asked to perform the coupling and decoupling procedures at least three times, until they felt comfortable with it. After training, all participants started with a baseline run, that is, without the automated system, hence normal manual truck driving (MD). This was a normal drive on the same road as they would drive on in the conditions with the system. After the baseline trial, the experimental session testing automated driving conditions (AD) began. In total, each participant conducted eight AD trials under different conditions. In this paper, we only report results about the last trial where the see-through truck condition and a critical event were included.

In the critical event trials, 10 participants drove behind a normal lead truck and 12 drove behind a lead truck which had a simulated screen attached to the rear of the truck showing the images of the road before the lead truck, thus giving the impression of a see-through truck (see Figure 6.1). Shortly after the beginning of the trial, the participants pressed the button to activate the automation system and follow the lead truck at a short distance of 0.3 s time headway. In order to have the largest chance of a proper driver response, the participants were instructed to be attentive of the traffic during this scenario. After 6500 m (approx. 5 min after the activation of the system) a visual/auditory warning was issued that the control was switched back to manual control. Immediately afterwards, the lead truck made an emergency manoeuvre either to the left lane (50% of the cases) or to the emergency lane (50%). A stationary vehicle was positioned 200 m from the onset of the warning (approx. 6.5 s to collision if no reaction was taken). After pressing the button to reclaim manual control, the drivers could either brake, or steer to the adjacent lane to avoid an accident. An overview of the experimental conditions is presented in Table 6.1.

Figure 6.1: Screenshot of a normal lead truck (left) and a see-through lead truck (right) in the simulation

Table 6.1: Overview of the experimental conditions

	Evading to the right	Evading to the left	N (participants)
Normal truck AD	x		5
Normal truck AD		x	5
See-through truck AD	x		6
See-through truck AD		x	6
Baseline MD			22

6.2.5 Dependent variables

6.2.5.1 Gaze behaviour

The analysis of visual behaviour was conducted comparing three conditions: following a see-through truck (AD), following a normal truck (AD) and baseline drive (MD). For both AD conditions, the time interval for analysis was the period when the automation system was activated. An equivalent time interval was chosen for the manual driving condition to allow the comparison with the AD conditions. Four relevant Areas of Interest (AOIs) were defined: windshield, left mirror, dashboard and secondary screen (where system status and warning were displayed). Glances outside the defined AOIs are labelled “Others”. Three basic metrics according to ISO 15007 were utilized to gain an overview about drivers’ information acquisition: percent time on AOI, mean glance duration and glance rate. These measures facilitate the understanding of driver monitoring pattern and enable quantitative comparison between the conditions. Since the windshield is the largest and most important AOI representing a driver’s forward view, and one glance onto this area may contain multiple fixations, a further analysis was conducted for the fixations located within this area for a deeper insight. A three-dimensional figure was plotted for each condition combining the positions of the fixations and the corresponding fixation durations, aiming to show an intuitive picture of drivers’ gaze patterns when monitoring the traffic environment.

6.2.5.2 Response to Critical Event

Analyses for the takeover performance was only conducted for two AD conditions. Regarding timing aspects, driver response time (RT) was measured, defined as the time interval from the warning onset until the first conscious intervention was taken, either by pressing the brake pedal for more than 10% or changing the steering angle more than 2°, whichever happened first counted. Quality were evaluated by the maximum brake accelerations, maximum steering angle and the minimum occurring time to collision (min TTC) within each condition. It was assumed that less harsh braking and smaller steering angles are equivalent to a less dynamic manoeuvre. Min TTC is an objective measure to assess the criticality to the situations. Larger min TTC indicates longer time left to avoid a collision with the obstacle, and therefore a safer handling. In summary, early intervention, less severe manoeuvres and larger minimum TTC indicate better performance.

6.3 Results and Discussion

6.3.1 Gaze behaviour

Two participants in the see-through truck condition and five participants in the baseline condition were omitted from the analysis due to missing data in eye-tracking recordings. To gain an overview about drivers’ attention allocation, the percent time on AOI was first presented in Figure 6.2, based on total glance times for all participants within each condition. Results showed when driving manually, the drivers devoted the largest percentage of their attention on the road (85% within all conditions). When following the normal lead truck, the participants showed the lowest percentage of time of eyes on the road (62%), and spent around one third of the total time looking at undefined areas. By checking video recordings, we concluded that they were predominantly looking outside the left window, which was out of the recording range of the eye-tracking system. When following the see-through truck, 73% of their time was spent monitoring the road, which is 11.3% more compared to driving behind a normal truck. In both AD conditions, the participants spent slightly more time checking the mirror, but less time monitoring the dashboard.

Figure 6.3 and Figure 6.4 show mean glance durations and glance rates regarding different AOIs. Due to the fact that not all participants looked at the left mirror, dashboard or secondary screen throughout the experiment, statistical tests were only intended for glances onto the windshield for the three conditions. Two one-way ANOVA tests were conducted, showing significant differences between groups in terms of mean glance duration (F (2,33) = 3.36, p = .047), while no significant differences were found. A Bonferroni post hoc test revealed that when driving behind a see-through truck, the mean glance duration onto the windshield was significantly longer than following a normal truck (p = 0.043). Differences between other conditions were not significant.

Figure 6.5 shows how the drivers distributed their attention within the windshield area. The position of each fixation point was illustrated on an x/y plane according to their world coordination in the eye-tracking system. The blue rectangle on this plane represented the configuration of the windshield. The duration of each fixation was also visualized on the z-axis. As can be seen from the 3D figure, when driving manually and following a see-through truck, the participants concentrated more on the road centre area (the left part of the rectangle) with longer fixation durations. Some extreme values were even above 6 s. When following a normal truck, drivers showed the similar tendency to focus more on the road centre, but the fixations were shorter and more dispersed.

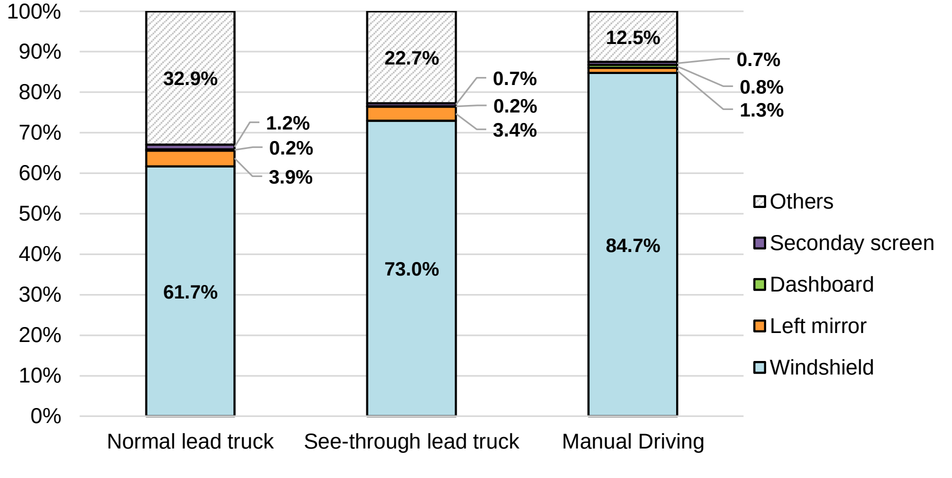

Figure 6.2: Percent time on AOIs compared across groups

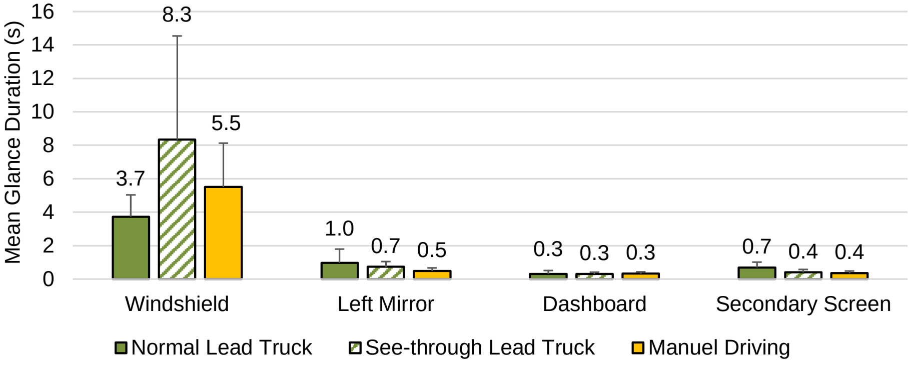

Figure 6.3: Mean glance duration on AOIs compared across groups

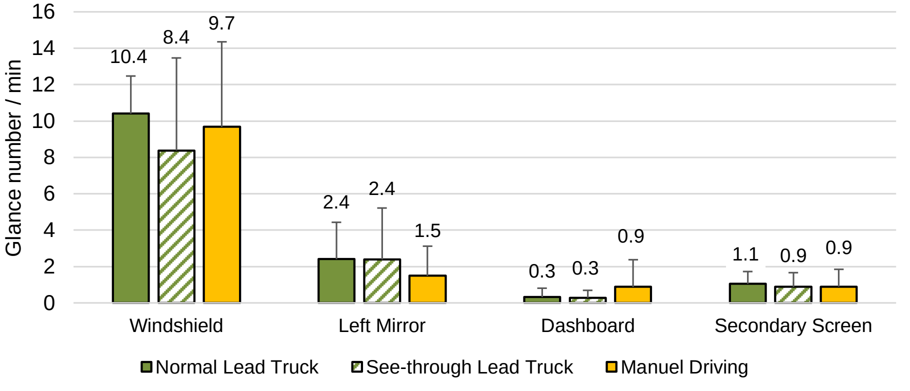

Figure 6.4: Glance rate on AOIs compared across groups

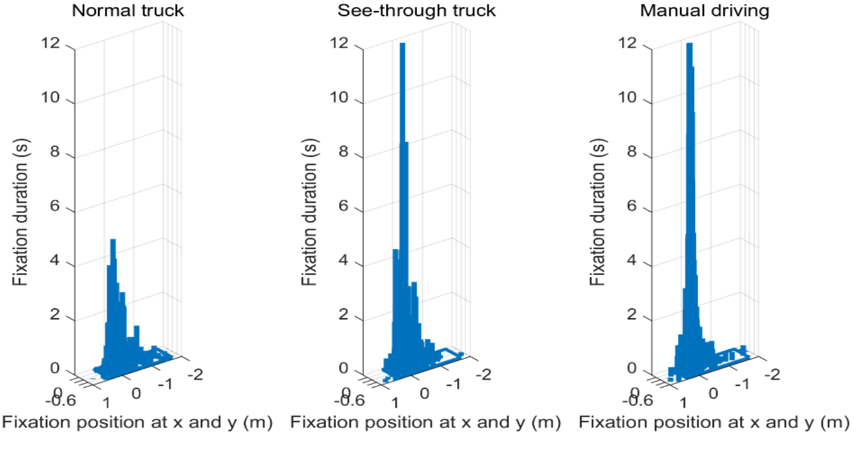

Figure 6.5: Fixations on the windshield. The positions of each fixation point are illustrated on an x/y plane according to their world coordination. The values on the z-axis indicate the corresponding fixation durations.

Combining the results above, the implementation of the see-through truck significantly increased the amount of attention allocated on the road, especially the centre area where the screen was located. These differences are mainly caused by longer single forward glances rather than more frequent fixations of the eyes. Furthermore, it can be inferred that when following a see-through truck, a driver's gaze behaviour is more similar to that during manual driving. Since the drivers were not instructed to do any secondary tasks, the behaviour of shifting attention away from the road implied a vigilance decrement when conducting the monitoring task. The shorter eyes-off-road time of the drivers in the see-through truck group indicated a higher level of attentiveness and more active monitoring. The first hypothesis is therefore supported and the results suggest a positive effect of the see-through truck on driver monitoring behaviour.

6.3.2 Response to the Critical Event

We measured driver performance metrics within 10 s after the warning onset. All participants successfully avoided a collision with the stationary truck. Table 6.2 gives a descriptive overview of driver reaction types in response to the critical event. Seven out of ten drivers stayed in the right lane and braked in order to avoid the stationary truck when following a normal truck (70%). One of the three drivers who did a lane change braked to full stop in the adjacent lane and didn't pass the obstacle. For the see-through truck, four out of 12 drivers changed lanes (33%).

Table 6.2: Numbers of participants who conducted three reaction types in each condition

	Brake	Lane change without deceleration	Lane change with deceleration
Normal Truck	7/10	2/10	1/10
See-through truck	8/12	2/12	2/12

Table 6.3 contains the means and standard deviations for the takeover quality measures, and the results of the independent t-test for the comparison between groups. For the three vehicle related measures, results are reported only for the participants who did not conduct evasion manoeuvres in order to avoid biases, because the operations on the brake pedal and steering wheel during lane changing are not comparable to those during braking in the ego lane. The only exception is to include the participant that conducted a harsh brake after a lane change in the analysis of max. braking acceleration.

Table 6.3: Means and standard deviations for response times, minimum TTC, maximal brake acceleration and maximum steering wheel angle (SWA), and t-test results for the comparison between groups

	Normal Truck	See-through Truck	t-test results
Response time (s)	M = 2.70 SD = 0.55	M = 2.89 SD = 0.64	t(20) = -0.728, p = 0.475
min TTC (s)	M = 4.42 SD = 0.79	M = 4.13 SD = 0.66	t(13) = 1.059, p = 0.309
max. a_{break} (m/s^2)	M = 6.14 SD = 0.27	M = 5.28 SD = 0.96	t(14) = 2.280, p = 0.039*
max. SWA (deg.)	M=14.65 SD = 3.58	M = 12.62 SD = 8.03	t(13) = 2.439, p = 0.030*

Contrary to our expectation, the drivers in the see-through truck condition did not intervene faster in response to the takeover event. Similarly, no significant differences were found regarding min TTC. Significant effects of the see-through truck were found when comparing maximum brake acceleration and maximum SWA, with smaller values for both measures in the see-through group. Therefore, a mixed answer was obtained when testing our second hypothesis. It seems that the implementation of see-through lead truck could be associated with less dynamic response manoeuvres, but did not evoke earlier intervention responses. Seen from the min TTC and the fact that no collision occurred, the situation never became really critical for the participants so a faster response might not be necessary. Another explanation can be that the participants in the see-through truck group already detected the obstacle before the warning, so they could better prepare themselves for a moderate response manoeuvre. Previous work of Gold, Damböck, Lorenz, & Bengler (2013) suggested a faster reaction within a short time budget could be accompanied with worse quality. The extra time budget gained from monitoring the see-through screen might have encouraged the participants to take slower, but less severe responses. These assumptions need further elaboration to be tested.

6.4 Conclusion and Outlook

In summary, despite the limited number of participants, a positive effect of the see-through truck can be suggested, with the participants allocating more time monitoring the traffic and responding less severely when encountering a critical event within comparable safety boundaries. This study also provided insight in possible safety issues in case of unforeseen scenarios. Even though drivers showed to be capable of responding appropriately when actively monitoring the environment, there are large individual differences in response times and type of response. Further research will need to focus on the individual differences between truck drivers, on other types of critical situations and on responses when a driver has been out of the loop when distracted by secondary tasks which will be a normal situation in future truck platooning concepts. In addition, the see-through truck tested in the current study has its drawbacks such as high cost and vulnerability to damage. It would be of interest to investigate the effects of in-vehicle see-through displays implemented in truck platooning in future studies.

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7. The effects of monitoring requests on driver attention, take-over performance, and acceptance

This chapter is based on the following two papers:

1) Lu, Z*., Zhang, B*., Feldhütter, A., Happee, R., Martens, H. M., & De Winter, J. C. F. (2019). Beyond mere take-over requests: The effects of monitoring requests on driver attention, take-over performance, and acceptance. *Transportation Research Part F: Traffic Psychology and Behaviour*, *63*, 22 -37. (*joint first authors).

2) Zhang, B., Lu, Z., Happee, R., De Winter, J. F. C., Martens, M. H. (2019). *Compliance with Monitoring Requests, Biomechanical Readiness, and Take-Over Performance: Video Analysis from a Simulator Study*. Paper presented at the 13th ITS European Congress, Brainport Eindhoven, The Netherlands.

7.1 Introduction

7.1.1 Level 2 and 3 automated driving

Automated driving is gradually being introduced to the market and may bring benefits to traffic safety, travel comfort, traffic flow, and energy consumption (Fagnant & Kockelman, 2015; Kühn & Hannawald, 2014; Kyriakidis, Happee, & De Winter, 2015; Meyer & Deix, 2014; Watzenig & Horn, 2017). A number of car manufacturers have released partially automated driving technology (Level 2 automation as defined by SAE International, 2016), combining adaptive cruise control with a lane keeping system. Partially automated driving still requires the driver to monitor the road and be able to take immediate control at all times. Manufacturers and scientists are now working towards a higher level of automation (i.e., SAE Level 3 ‘conditional automation’) in which the system is capable of driving in certain conditions and the driver does not have to monitor the road anymore. In case the system reaches its operational limits, the driver has to take control in response to a take-over request (TOR).

7.1.2 The demanding time budgets of take-over requests

When taking over control, drivers need time to acquire situation awareness (Lu, Coster, & De Winter, 2017; Samuel, Borowsky, Zilberstein, & Fisher, 2016) and physically prepare for taking over control (Large, Burnett, Morris, Muthumani, & Matthias, 2017; Zeeb, Härtel, Buchner, & Schrauf, 2017; Zhang, Wilschut, Willemsen, & Martens, 2019). A large body of research has confirmed the importance of the time budget, defined as the available time between the TOR and colliding with an obstacle or crossing a safety boundary (see Eriksson & Stanton, 2017; Zhang, De Winter, Varotto, Happee, & Martens, 2019, for reviews). While time budgets between 5 and 7 s are often used (Zhang, De Winter et al., 2019), how much time drivers need for taking over control may depend on the driving task and context. Mok, Johns, Miller, and Ju (2017) showed that almost all drivers crashed when the time budget was only 2 s, whereas Lu et al. (2017) showed improvements in situation awareness up to 20 s of time budget.

In on-road settings, a TOR with a long time budget cannot always be provided. If the automation relies on radars or cameras to detect a collision with other road users, the achievable time budget of the TOR depends on the predictability of the unfolding situation and the capabilities of the sensors, which implies that the time budget between the TOR and the collision is usually short. In a review about human-machine interfaces in automated driving, Carsten and Martens (2018) explained that it is often unfeasible for the automated driving system to indicate in sufficient time that human intervention will be needed, which ‘‘necessitates constant monitoring by the human, so that a system that is supposed to be relaxing may actually be quite demanding”.

7.1.3 Monitoring requests and uncertainty presentation

In a review on transitions in automated driving from a human factors perspective (Lu, Happee, Cabrall, Kyriakidis, & De Winter, 2016), transitions in automated driving were classified into two types: control transitions and monitoring transitions. Lu et al. (2016) argued that much of the human factors literature has focused on control transitions (e.g., studies of take-over time), and pointed out that the two transition types can occur independently. For example, the driver may decide to monitor the road and achieve situation awareness, without necessarily taking over control.

Gold, Lorenz, Damböck, and Bengler (2013) previously implemented the concept of monitoring requests (MRs) in a driving simulator with the aim to achieve a monitoring transition that prepares drivers for a possible TOR. In their study, a TOR was provided if an uncertain situation became critical (i.e., a pedestrian or object entering the lane of the ego vehicle). The participants were instructed to monitor with their eyes only or keep their hands on the steering wheel in addition. Results showed shorter take-over times and fewer cases of no intervention when the participants were monitoring ‘hands on’ as compared to visual-only monitoring. By comparing to one of their previous studies (Gold, Damböck, Lorenz, & Bengler, 2013), the authors suggested that the MR concept is effective in terms of safety. Louw, Markkula et al. (2017) and Louw, Madigan, Carsten, and Merat (2017) applied a concept in which an uncertainty alert was implemented upon the detection of a lead vehicle. The lead vehicle could decelerate, accelerate, or change lanes, and participants had to decide themselves whether to take over, as no TOR was provided. The two studies by Louw et al. examined relationships between drivers’ eye movement patterns and crashes outcomes. However, an evaluation of the uncertainty alarm was not within their research scope. Summarizing, based on the above studies, it seems that the provision of MRs is viable in automated driving. However, the above studies did not directly compare the effects of the MR concept with a system that provides only a TOR. It would be relevant to make such a comparison and examine whether MRs prepare drivers to take over control safely in response to a subsequent TOR.

Herein, we evaluated a concept where, in addition to issuing a TOR, we provided an MR when approaching a critical location. Such an MR concept would rely not on camera/radar/lidar, but on basic localization (e.g., differential GPS, HD maps). That is, the MR could be applied when approaching a segment of the road where TORs are likely to occur (e.g., an intersection, zebra crossing, or construction works). The automation system thus degrades itself from Level 3 to Level 2 by promoting a temporary monitoring transition when it is uncertain of the (upcoming) environment, instead of changing from Level 3 to manual driving directly. The idea of an MR is that a driver is primed to take-over control but does not necessarily have to take over control.

In the literature, several concepts exist that are similar to MRs. Outside of the domain of driving, likelihood alarm systems (LAS) have been devised, which issue different types of notifications depending on the likelihood that a critical event occurs (e.g., Balaud, 2015; Wiczorek, Balaud, & Manzey, 2015). Also in driving research, concepts have been designed that intermittently or continuously inform the driver and accordingly ensure that drivers are prepared to reclaim manual control. For example, in a driving simulator study, Beller, Heesen, and Vollrath (2013) presented an uncertainty symbol in unclear situations (when the front vehicle was driving in the middle of the two lanes). No TOR was available and the participants had to decide themselves whether to intervene or not. Compared to without such an uncertainty symbol, the participants intervened with a longer time to collision (TTC) in case of automation failure. Other examples are a LED bar on the instrument cluster indicating the momentary abilities of the automation (Helldin, Falkman, Riveiro, & Davidsson, 2013; Large et al., 2017), an ambient LED strip changing colour or blinking pattern based on hazard uncertainty information (Dziennus, Kelsch, & Schieben, 2016; Yang et al., 2017), a continuous verbal notification informing the driver about the state of the ego car and the behaviour of other road users (Cohen-Lazry, Borowsky, & Oron-Gilad, 2017), and a lane-line tracking confidence notification (Tijerina, Blommer, Curry, Swaminathan, Kochhar, & Talamonti, 2017). The results of these studies showed that participants who were provided with the uncertainty indication were better prepared in critical situations (Dziennus et al., 2016; Helldin et al., 2013; Yang et al., 2017). However, there are also a number of potential shortcomings of uncertainty presentations. In particular, continuous displays require driver attention and may hinder engagement in non-driving tasks. Conversely, drivers may neglect such displays when they wish to perform a non-driving task (Cohen-Lazry et al., 2017; Yang et al., 2017).

Finally, it is noted that a number of studies have used the concept of ‘‘soft-TOR” or ‘‘two-step TOR” to acquire the driver’s attention before taking over control (Lapoehn et al., 2016; Naujoks, Purucker, Neukum, Wolter, & Steiger, 2015; Van den Beukel, Van der Voort, & Eger, 2016; Willemsen, Stuiver, & Hogema, 2015; and see Brandenburg & Epple, 2018 for a questionnaire study). Two-step TORs differ from MRs because with a two-step TOR, the driver always has to take over after receiving the notification, whereas this is not necessarily the case with the MR concept.

7.1.4 Compliance

For a warning system to be effective, it is essential to “provide the opportunity for protective behaviour to occur before a threat materializes” (Breznitz, 1984). Compliance plays a central role because it reflects the operator’s willingness to perform protective/preparatory behaviour in response to a warning signal (Meyer, 2004; Lees & Lee, 2007). When a warning is issued for something that does not actually occur, a decrease in compliance in the following warning phases might take place, a phenomenon also known as the false alarm effect or cry-wolf effect (Breznitz, 1984; Sorkin, 1988; Dixon, Wickens, & McCarley, 2007; Wickens, Dixon, Goh, & Hammer, 2005; Zabyshny & Ragland, 2003). In Breznitz’ experiments that extensively explored the cry-wolf effect, an electric shock threat was announced by a three-minute warning, then cancelled out by the experimenter (i.e., the experimenter announced that the shock would not occur). During the warning phase, the participants could reduce the intensity of the impending electric shock by pressing a pedal at some monetary cost, which represented protective behaviour against the pain. The session was repeated three times. Using three indices to quantify protective behaviour, Breznitz found reductions in the probability and amplitude of protective behaviour (i.e., whether the participants pressed the pedal; if so, how many times the pedal was pressed), as well as an increase in latency between the alarm onset and the initiation of the protective action. Besides being one of the first demonstrations that false alarms reduce compliance, Breznitz further pointed to dynamic patterns of the compliance level: compliance may decrease with consecutive false alarms, and increase significantly after a true alarm.

In the automotive domain, studies have mainly investigated drivers’ compliance with imperfect collision warning systems (e.g., Bliss & Acton, 2000, 2003; Cotté, Meyer, & Coughlin 2001; Lees & Lee, 2007; Naujoks, Kiesel, & Neukum, 2016). In line with Breznitz (1984), results suggest that false alarms substantially decrease driver compliance (e.g., lower response frequency, slower braking response, and smaller reductions of speed). A few researchers have distinguished between true false alarms and unnecessary alarms based on the context in which the alarm occurs. While true false alarms are caused by detection errors, unnecessary alarms are issued as intended (e.g., associated with the driving context) but the threat resolves before intervention is needed (e.g., a pedestrian stood on the roadside but later decided not to cross the road). According to Breznitz (1984), both alarm types will cause cry-wolf effects because either the warning or the threat loses credibility. The magnitude of the cry-wolf effect, however, may differ between the two alarm types. In a comparison of false alarms and unnecessary alarms, Lees and Lee (2007) reported more frequent brake responses and larger speed reductions with unnecessary collision alarms and concluded that unnecessary alarms do not diminish compliance because they are comprehensible to the driver. Naujoks et al. (2016) documented a similar differential influence of the two alarm types.

In this study, questions related to driver compliance need to be raised, because only a small portion out of all MRs require an actual driver take-over. The MR implemented in this study notified drivers while entering locations where a take-over was likely to be requested; therefore the MRs that are not followed by TORs are likely to be perceived as unnecessary alarms rather than false alarms. MRs are also different from the aforementioned collision warnings in that MRs request attention and preparation, rather than driver intervention. It needs to be investigated whether drivers exhibit “cry-wolf” effects when using uncertainty notifications, and how drivers’ compliance with a MR affects their take-over performance if a critical event indeed occurs.

7.1.5 Reliance effects

In the cry-wolf effect, Type I errors (false alarms) cause a reduction in reliance. The opposite effect is also possible: if warnings unfailingly require a response, the operator may develop (over)reliance on those warnings, which can be manifested by so-called errors of omission (i.e., not responding when there is no warning) or errors of commission (i.e., complacently responding to a warning that is inappropriate in the given context) (Skitka, Mosier, & Burdick, 1999). Accordingly, it can be argued that any study on in-vehicle warnings ought to include an evaluation of drivers’ reliance and trust. An on-road study by Victor et al. (2018) suggests that drivers may fail to act despite being alerted and having their eyes on the road. Thus, there is a certain risk that drivers may not act in a critical situation when the system fails to provide a TOR, despite the fact that an MR is presented beforehand. In the present study, we also examined whether drivers over-relied on the TOR, despite the fact that they were being forewarned by means of an MR.

7.1.6 Aim of the study

In summary, the concepts of uncertainty presentation and MRs are promising, as they can increase situation awareness and cognitively and physically prepare drivers to intervene when needed. However, the literature also points to potential risks in terms of distraction. At present, it is unknown whether an MR works as intended by priming drivers to take-over control if needed. A successful MR system should ensure that drivers respond quickly to a subsequent TOR, and ensure that drivers do not take over if no critical event occurs. Furthermore, it is unknown whether drivers would accept a concept that intermittently requests them to monitor the road.

In this study, a system was implemented that intends to direct the driver’s attention to the road by means of an MR when the automation enters a location where a take-over is likely to occur (i.e., a zebra crossing, where pedestrians could sometimes cross the road). The driver’s monitoring state (i.e., whether the driver responded by attending to the road and touching the steering wheel), driving performance (braking and steering behaviour in response to a TOR presented after the MR), as well as subjective experience (a variety of human constructs such as workload and trust, Parasuraman, Sheridan, & Wickens, 2008) using such an MR + TOR system were compared with a baseline system which presented only a TOR. Accordingly, the aim of this study was to investigate whether drivers are responsive to the MR by looking at the road when requested, whether drivers do not unnecessarily take over control when no action is needed (when no pedestrians cross the road), and whether drivers have a shorter take-over time when being forewarned by the MR as compared to when receiving only a TOR.

Additionally, we examined if the participants’ compliance with MRs changed with previously experienced scenarios, and if they exhibited over-reliance on the TORs. To examine drivers’ compliance with MRs, we first looked into how drivers prepared themselves for a potential take-over event in response to the MR. Second, we examined whether drivers’ preparatory behaviour decreased after unnecessary MRs (i.e., no take-over required) and increased after experiencing a take-over event. Third, we examined whether drivers’ preparatory behaviour was associated with take-over performance.

To examine whether drivers' exhibited over-reliance on the TORs, we included a final trial where an MR was presented, but no TOR followed. This scenario is realistic: As explained above, in some cases, the sensors of the automated driving system may not detect the hazard, and no TOR can be provided. Accordingly, we examined whether drivers failed to respond to a hazard (i.e., an error of omission) in an MR-only scenario in comparison to an MR + TOR scenario.

7.2 Methods

7.2.1 Participants

Forty-one participants (35 males, 6 females) were recruited through Facebook and university whiteboard advertisements of the Technical University of Munich. Their mean age was 29.6 years (SD = 7.0, ranging from 20 to 57 years). All participants had valid driving licenses (which were held for 11.2 years on average, SD = 7.2). Participants were compensated with 10 euros.

Of the 41 participants, 4 participants had experience with driving in a simulator prior to this study. Furthermore, 18, 12, and 6 participants reported prior experience with adaptive cruise control, a lane keeping system, and partially automated driving, respectively. All participants provided written informed consent, and the research was approved by the Human Research Ethics Committee (HREC) of the Delft University of Technology.

7.2.2 Apparatus

The study was conducted in a static driving simulator located at the Technical University of Munich, Germany. The simulator consists of a BMW 6-Series vehicle mock-up, and provides an approximately 180 degrees field of view. Three projectors provided views for the rear-view mirrors. The software for simulating the driving scenarios was SILAB from WIVW GmbH, which recorded the vehicle data at a frequency of 120 Hz. The automated driving system controlled longitudinal and lateral motion, and could be activated and deactivated by pressing a button on the steering wheel. The sound effects of the engine, passing vehicles, as well as warnings, were provided via speakers of the vehicle cabin. A dashboard mounted eye tracking system (Smart Eye) was used to record participants' eye movement at a frequency of 60 Hz. The driver's glance locations were classified into the following areas of interest (AOI): windshield (road in front of the driver), central console, left and right exterior mirror, rear-mirror, and instrument cluster. A 9.5 by 7.31-in. handheld tablet (iPad 2) was provided to the participants for performing a non-driving task. The vehicle and the cabin are shown in Figure 7.1.

Figure 7.1: The TU Munich Driving Simulator. Left: full-vehicle mock-up; Right: cabin.

7.2.3 Automation system and human-machine interface

In the basis of the experiment, two automation systems were tested: (1) MR + TOR: automation with take-over requests (TOR) being preceded by monitoring requests (MR) and (2) TOR-only: automation with TOR but without MR. The third condition (MR-only) was presented last to investigate whether the participants had developed over-reliance on the TOR signal.

The MR + TOR system consisted of five automation states, with corresponding status icons shown on the dashboard (Figure 7.2 and Figure 7.3). When the automation was unavailable, a white car on a light blue road was shown in the top centre (Figure 7.2a) and the driver needed to drive manually. When the requirements for automated driving were fulfilled, a verbal notification ‘‘Automation available” was issued, and a green steering wheel icon was shown (Figure 7.2b). The driver could press a button on the steering wheel to activate the automation (the icon then changed to Figure 7.2c with an acoustic state changing sound, i.e., a gong). When the automation was active, the participant could take the hands off the wheel and feet off the pedals.

When entering an area in which a critical situation might occur, the system issued an MR. The MR consisted of a gong sound followed by a verbal notification ‘‘Please monitor”, and a yellow eye-shaped icon (Figure 7.2d). The automation remained fully functional after the MR onset. If no critical event occurred, the MR was dismissed after passing the zebra crossing, and the icon changed back to the ‘automation activated’ state (Figure 7.2c) accompanied by a gong sound.

If the system detected a situation that it could not handle, a TOR was provided, and the automation was deactivated at the same time, leading to a slight deceleration. The acoustic TOR warning was a sharp double beep (75 dB, 2800 Hz) followed by a verbal take-over request ‘‘Please take-over”. Figure 7.2e. Figure 7.3 (right) show the visual display for the TOR: an orange hands-on-the-wheel icon in the lower center of the dashboard, and the automation state icon back to ‘‘automation unavailable” (Figure 7.2a). Upon receiving the TOR, the driver had to take over by braking and/or steering in response to the situation. After taking over control, the driver had to drive manually until the automation became available again; they could then reactivate the automation. The TOR-only system was identical to the MR + TOR system, except that there was no MR. In addition, the participants drove a third condition (MR-only), in which an MR but no TOR was provided before a critical event.

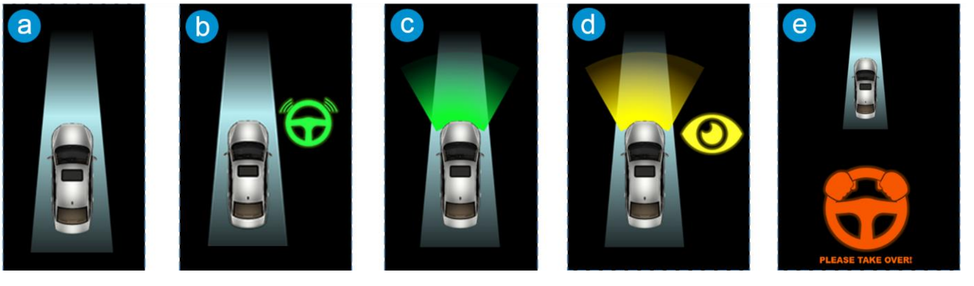

Figure 7.2: Screenshots of the visual interface for the five system states. a) automation unavailable; b) automation available but not yet activated; c) automation activated; d) monitoring request; e) take-over request.

Figure 7.3: Photos of the instrument cluster with automation status. Left: automation available, corresponding to Figure 7.2 b; Right: take-over request, corresponding to Figure 7.2 e.

7.2.4 Experimental design and test scenarios

A within-subject design was used, meaning that each participant completed all three conditions (MR + TOR, TOR-only, and MR-only) in three separate sessions. The order of the MR + TOR and TOR-only conditions was counterbalanced, whereas the MR-only condition was always presented in the last (i.e., third) session.

The simulated experimental track consisted of rural and city road segments with one lane in each direction. There was moderate traffic in the opposite direction and no traffic in the ego lane. The speed limit was 80 km/h on the rural road and 50 km/h in the city, as indicated by speed limit signs along the road. The automation drove at a constant speed of 80 and 50 km/h in the corresponding segments (except for the deceleration and acceleration between the city and rural roads). The critical events that required driver intervention were pedestrians who were crossing at a zebra crossing in the city road segments. Due to the layout and kinematics of the situation, braking was the required and expected action to avoid a collision, although some optional steering could be applied as well. The participants were not informed about the specific situation, and were told to respond by either steering or braking depending on their judgement. In the MR + TOR condition as well as the TOR-only condition, five zebra crossings were included. At two out of five crossings, two pedestrians stood behind an obstacle (either a bus stop or a truck) on the pavement, 1.5 m from being visible to the participant in the walking direction. The first crossing pedestrian started walking at a speed of 1.5 m/s when the participant's car was 83.33 m away from the zebra crossings (TTC = 6 s at 50 km/h). The other pedestrian crossed the road with a speed of 1 m/s, following the first pedestrian (Figure 7.4 Left). It took around 5 s for the first pedestrian and 9 s for the second pedestrian to cross the road. No pedestrians were present at the other three crossings, and the participants were not supposed to take over (Figure 7.4 Right).

The MR-only condition contained three zebra crossings. There were no pedestrians at the first two crossings. At the last crossing, two pedestrians started crossing the road 7 s after the MR was announced, but no TOR was given. This session ended after the critical event. The session of the MR-only condition lasted approximately 10 min. Figure 7.5 provides an illustration of the order of sessions and events for one participant.

Figure 7.4: Left: Zebra crossing with two pedestrians crossing the road (a take-over scenario). Right: Zebra crossing without pedestrians (here, it was not necessary to intervene). Note that these screenshots were taken from an observer's perspective in the simulator software, not from the driver's perspective.

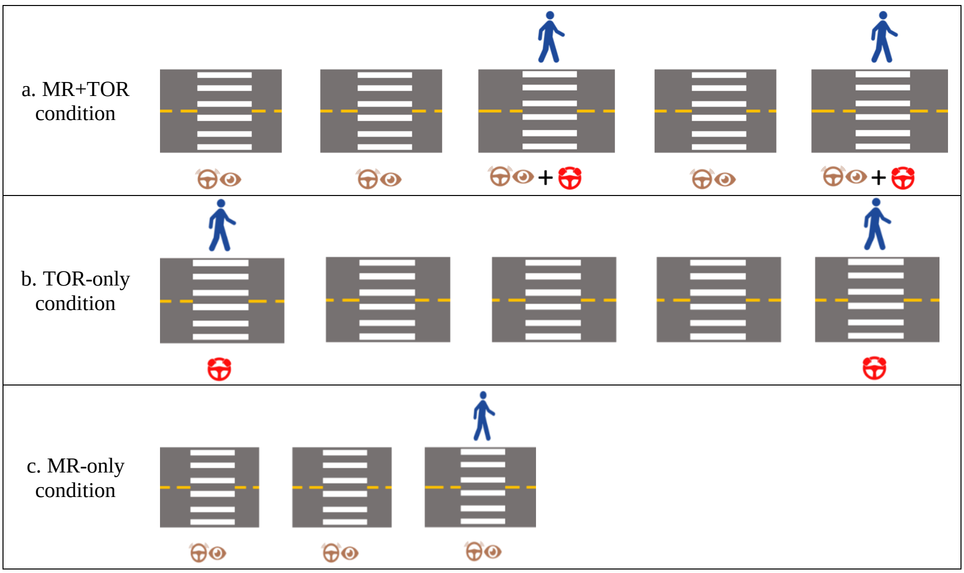

Figure 7.5: Illustration of the order the sessions and events for one participant. The MR+TOR and TOR-only conditions were counterbalanced, and the MR-only condition was always driven after the first two conditions. The sequences of the five scenarios in MR+TOR and TOR-only conditions were randomized for each participant. The sequence of the three scenarios in the MR-only condition was fixed as shown in c).

7.2.5 Non-driving tasks

The participants were instructed to play Angry Birds or Candy Crush (visual-motor tasks without sound) during automated driving on a handheld tablet PC (iPad 2) provided by the instructor. These games are self-paced and interruptible (Naujoks, Befelein, Wiedemann, & Neukum, 2017), meaning that participants could pause the game whenever they felt necessary to look up to the road.

7.2.6 Procedures

Upon arrival at the institute, the participants were welcomed and asked to read a consent form. The first part of the form contained an introduction to the experiment and the two automation systems. The form mentioned that participants would experience two systems: one with and one without the MR in the first two sessions, and that they would again experience the system with the MR in the third session. Moreover, they were informed that, in all three sessions, the TOR would be available if the critical events are detected successfully. The participants were instructed to keep their hands off the steering wheel and feet off the pedals during highly automated driving. Furthermore, they were asked to play the game during the experiment, and stop playing when the automation requests them to take control. They were also informed to stop playing the game and monitor the surroundings whenever they feel insecure, even when the automation provides no request. Participants were not informed about the specific type of event that would occur (pedestrians crossing the road), nor about the fact that the system would fail to provide a TOR.

After signing the consent form, the participants completed a questionnaire regarding their age, gender, and driving experience. Next, a handout with pictures for each of the automation-status icons was provided, and the non-driving tasks were introduced on the tablet. The participants were then led to the driving simulator. The positions of the seat, mirrors, and the steering wheel were adjusted to each participant’s preference, and the eye-tracking system was calibrated.

At the beginning of the experiment, each participant drove a training session of approximately 4 minutes, during which they received verbal explanations from the experimenter. The participants started this training on a rural road and drove manually for around 2 minutes. Upon approaching an urban area, the participants received a notification from the system and pressed the button to activate the automation. In the urban area, the participant experienced an MR when approaching a zebra crossing without a critical event. Shortly afterwards, the participants received another MR and subsequently a TOR because of road construction ahead. The participant had to take over control by braking or steering to avoid a collision with the traffic cones in the ego lane. The training session ended after the participant drove past the construction area.

Next, the participants drove the three experimental sessions described in section 2.4. Before the session, they were informed which of the two systems (TOR-only or MR+TOR) they were about to experience. After each session, the participants took a break and completed a questionnaire about their workload (NASA-TLX) when performing the experiment, and rated the automated driving system they just experienced. The entire experiment lasted approximately 90 min per participant.

7.2.7 Dependent variables

The drivers’ behaviour during this study was assessed using the data recorded by the eye tracker, simulator software and self-report questionnaires.

7.2.7.1 Eye movements

Two gaze-based measures were used in this study.

- Eyes-on-road response time: defined as the time interval from the MR onset until the first detected glance on the road. In the TOR-only condition, the eyes-on-road response time is the interval from the TOR onset until the first detected glance on the road.

• The percentage time eyes-on-road: the percentage of time that glances were within the area of the windshield when the automation was active (i.e., periods when the vehicle was within 166.67 m before the zebra crossings were excluded). This measure describes whether participants showed different monitoring behaviour (i.e., voluntarily looking at the road) when using the two automation systems.

Glances shorter than 0.125 s were eliminated from the raw tracking data, in approximate agreement with the minimum possible fixation duration (ISO, 2014).

7.2.7.2 Take-over performance measures

The following measures were used to evaluate how quickly the participants responded to the MR and TOR.

- Hands-on-wheel time: the time interval measured from the moment a pedestrian became visible (i.e., the TOR onset if available) until the participant put at least one hand on the steering wheel, as measured with detection sensors in the steering wheel.
- Brake initiation time: the time interval measured from the moment a pedestrian became visible (i.e., the TOR onset if available) until the first detectable braking movement (first non-zero brake signal).
- Steer initiation time: The time interval measured from the moment a pedestrian became visible (i.e., the TOR onset if available) until the first detectable steering movement before the zebra crossing (exceeding 0.02 radians).
- Minimum TTC: The minimum time to collision (TTC) in scenarios where pedestrians were crossing the road. This measure was calculated after the first moment the driver pressed the brake. The minimum TTC was zero if a collision occurred.
- Maximum longitudinal deceleration: The maximum deceleration in scenarios where pedestrians crossed the road. This measure was calculated for moments the driver pressed the brake.

7.2.7.3 Subjective measures

After each session, participants completed questionnaires concerning workload, acceptance, usability, and trust. All the scores were linearly scaled to percentages.

- Mental workload: the workload was measured using the NASA Task Load Index (NASA-TLX; Hart & Staveland, 1988), which consists of six dimensions: mental demand, physical demand, temporal demand, performance, effort, and frustration. Each of the six items had 20 markers, and ranged from “low” to “high”. In the analysis, the score for the performance item was reversed from “low” to “high” to “high” to “low”.

- Acceptance: the acceptance scale developed by Van der Laan, Heino, and De Waard (1997) consists of nine questions with items scored -2 to +2 on a 5-point semantic differential scale. Scores were calculated for two dimensions: Usefulness (1. useful–useless, 3. bad–good, 5. effective–superfluous, 7.assisting–worthless, and 9. raising alertness–sleep-inducing) and Satisfaction (2. pleasant–unpleasant, 4. nice–annoying, 6. irritating–likeable, 8. undesirable–desirable). In the calculation of the usefulness and satisfaction scores, the scores for items 1, 2, 4, 5, 7 and 9 were reversed.

- Usability: Usability of the human-machine interface was assessed based on Nielsen’s Attributes of Usability (Nielsen, 1994). The participants expressed their degree of agreement with five statements regarding learnability (learning to operate the system was easy for me), efficiency (my interaction with the system was clear and understandable), memorability (it was easy to remember how to use the system), accuracy (it was easy to use the system quickly without making errors) and subjective satisfaction (the system was easy and comfortable to use) on a seven-tick Likert scale from disagree to agree.

- Trust: Trust in automation system was assessed using five items selected from a questionnaire by Jian, Bisantz, & Drury (2000). The participants expressed their degree of agreement on a seven-tick Likert scale regarding mistrust (the system behaves in an underhanded manner), harm (the system's actions will have a harmful or injurious outcome), suspicion (I am suspicious of the system's intent action, or outputs), confidence (I am confident in the system) and security (The system provides security). Differences between the MR+TOR and TOR-only conditions were compared using paired t-tests, with a significance level of 0.05.

7.2.8 Driver compliance with MRs

The evaluation of driver compliance with MRs only concerns the MR + TOR session. To explore variability in driver compliance, the first three of five MR blocks were analysed. The participants were divided into four groups based on four possible combinations in their first two trials:

a) 1. MR-only, 2. MR-only

b) 1. MR-only, 2. MR+TOR

c) 1. MR+TOR, 2. MR-only

d) 1. MR+TOR, 2. MR+TOR

Accordingly, their prior experience when receiving an MR in the first three trials was as follows:

a) 1. First MR, 2. After one MR-only, 3. After two MR-only (see Figure 7.6 for illustration)

b) 1. First MR, 2. After one MR-only, 3. After TO

c) 1. First MR, 2. After TO, 3. After one-MR-only

d) 1. First MR, 2. After TO, 3. After TO.

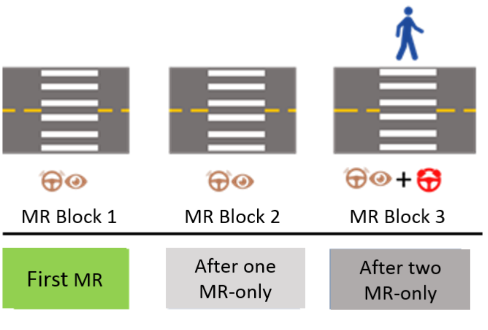

Figure 7.6: Example of the coding of blocks.

Because the MR aims to prepare the driver for a critical event, we measured the compliance with MR based on drivers' preparatory behaviours, which involved eye, hand, and foot movements. Breznitz's three indices of protective behaviour (see Introduction) were adopted to quantify drivers' preparatory behaviour, namely probability, latency, and amplitude. Detailed descriptions are listed in Table 7.1. The data were retrieved from manual video annotations. All observations started from the onset of the MR, with a duration of 7 s. Two independent raters (the first and second authors) rated the level of preparatory behaviour. The raters came to a consensus on all disagreements.

To determine associations between the level of preparatory behaviour and subsequent take-over performance, three performance measures were compared between preparation levels: 1) take-over time, measured from the onset of the TOR until the moment the driver started to press the brake pedal 2) minimum time to collision, calculated after the moment the driver pressed the brake pedal; 3) maximum deceleration calculated during the braking process.

Table 7.1: Measures of preparatory behaviour

Measures	Description		
	Eyes	Hands	Feet
Probability	The percentage of participants who looked up (any glance counts, regardless of the duration).	The percentage of participants whose hands were in a more convenient position for taking the steering wheel compared to when no preparation was made at all (i.e., Level of preparation > 0, as described below).	The percentage of participants whose feet were in a more convenient position for taking the steering wheel compared to when no preparation was made at all (i.e., Level of preparation > 0, as described below).
Latency	How long after the MR onset the participant started looking up.	How long after the MR onset the participant started moving their hands to be in a more convenient position for taking the steering wheel.	How long after the MR onset the participant started moving their foot to be in a more convenient position for pressing the braking pedal.
Amplitude	-	Level 0: Both hands were holding/interacting with the iPad/phone at the MR onset, with no obvious movement to put the iPad/phone away.	Level 0: The feet were placed far from the pedals at the MR onset, with no obvious indication to move one foot closer to the pedals.
		Level 1: The iPad was already placed on the lap at the MR onset, or the participant lowered the iPad on the lap after receiving the MR. Both hands were still holding/touching the edge of the iPad/phone, with no obvious movement to free the	Level 1: One foot was already placed close to the pedals at the MR onset, or the participant moved one foot closer to the pedals after receiving the MR, but not hovering above the brake pedal.

	hand(s) to be prepared to take the wheel.	
	Level 2: There was an obvious attempt to free at least one hand to be prepared to grab the steering wheel (e.g., putting the iPad on the passenger seat, or having one hand in the air).	Level 2: The foot was hovering above the brake pedal at the MR onset, or the participant put one foot on the braking pedal after receiving the MR.
	Level 3: At least one hand was touching the steering wheel at the MR onset, or the participant put at least one hand on the steering wheel after receiving the MR.	

7.3 Results

7.3.1 Missing values and excluded data

Of the 41 participants, two participants experienced severe simulator sickness, and one participant had difficulties understanding the operation of the automation system. These three participants were excluded from all analyses. Furthermore, one participant’s eye-tracking data was lost due to an experimenter’s error, and the gaze calibration for three participants was not performed properly. Their eye tracking data were excluded from the eye-tracking analysis. Summarising, the data analysis is based on the driving performance data and the self-report data from 38 participants, and the eye tracking data from 34 participants.

One event from one participant in the TOR-only condition was excluded from all analyses, because the automation was deactivated before the event. Furthermore, in the TOR-only condition, one collision with a pedestrian occurred. This collision occurred because the driver intentionally did not brake to determine whether the car could brake automatically, as was discovered during the interview after the experiment. Only the eye tracking data from this event were included in the analysis. In addition, the eyes-on-road response time of one event in the MR+TOR condition was excluded due to missing data. Table 7.2 provides an overview of the number of events and responses for the main part of the experiment, that is, the MR+TOR and the TOR-only conditions. It can be seen that the MR system generally worked as intended, as participants had their eyes on the road at the moment of the TOR in 61 out of 68 cases. In the remaining 7 cases, participants monitored the road but had their attention allocated back to the secondary task when the TOR was provided. Furthermore, in situations without pedestrians, braking occurred in only 1 out of 114 trials, and in situations with pedestrians, participants braked in all cases.

For the assessment of driver compliance with MRs, several video recordings were unavailable due to technical problems or poor visibility. The number of participants with complete probability/amplitude data for the first three blocks was 26 for hand preparation and 27 for foot preparation.

Table 7.2: Number of events and responses in the MR+TOR and TOR-only conditions.

Condition	Pedestrian-crossing scenarios	Total		Braking action	Full stop	Crash	Eyes on the road at the moment of the MR	Eyes on the road at the moment of the TOR
		Driving data included	Eye gaze data included					
MR+TOR	MR (i.e., no pedestrians)	114	102	1	0	—	14	—
	MR+TOR (i.e., with pedestrians)	76	68	76	50	0	9	61
TOR-only	TOR (with pedestrians)	74	67	74	50	1	—	15

7.3.2 Gaze behaviour

We analysed the allocation of the participants' eyes on the road and instrument cluster while they were approaching the zebra crossings. Response times were calculated starting with the onset of the TOR and MR. The visualizations were performed using the position of the participant's car on the x-axis, since the TOR/MR was triggered based on the position of the car, which is consistent with how sensors work in real systems. Furthermore, by using distance instead of time on the x-axis, spatial relationships can be assessed intuitively; this would be impossible when using time on the x-axis, as different participants take different amounts of time to complete the scenario, depending on how they brake and use the throttle to accelerate again.

Figure 7.6 shows how the participants shifted their attention back to the road after receiving an MR or TOR as a function of travelled distance, for three scenarios: MR without pedestrians crossing the road, MR followed by a TOR (i.e., pedestrians crossing the road), and TOR in TOR-only conditions (i.e., without an MR).

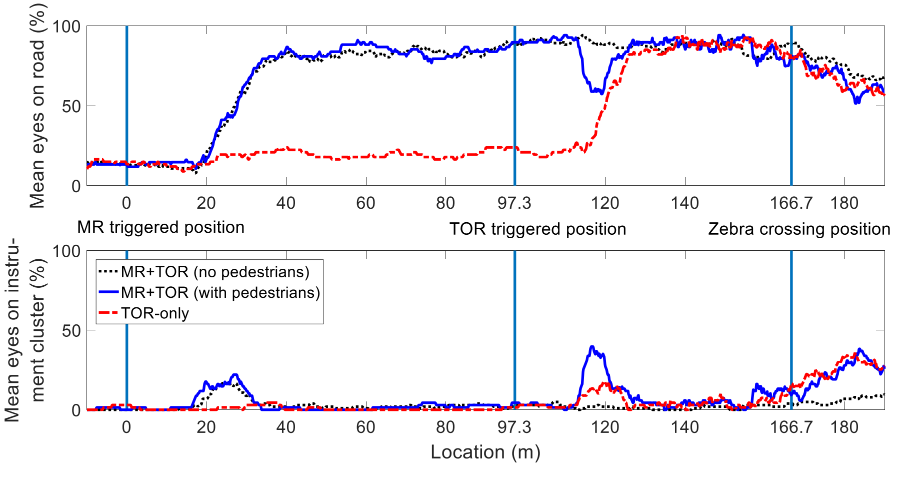

Figure 7.7: Participants' visual attention allocation on the windshield (upper plot) and instrument cluster (lower plot) for the MR+TOR and TOR-only conditions. Three vertical lines from left to right are the locations of the MR (0 m; time to zebra crossing = 12 s), TOR (97.3 m; time to zebra crossing = 5 s), and zebra crossing (166.7 m).

From Figure 7.7, it can be seen that participants, on the aggregate, showed an eye-movement response towards the road and instrument cluster between 20 m to 40 m after the onset of an MR (in the MR+TOR condition) or a TOR (in the TOR-only condition). After passing the zebra crossing, some participants shifted their attention from the road to the instrument cluster. This attention shift to the instrument cluster may be because participants attempted to assess their speed or the automation status when accelerating again, after having braked for the pedestrians (see Figure 7.8 for a figure with the mean speed).

The mean eyes-on-road response time to MRs in the MR+TOR condition was 1.85 s (SD = 0.51 s), whereas the eyes-on-road response time to the TOR in the TOR-only condition was 1.76 s (SD = 0.73 s) (after removing 23 from 170 events in the MR+TOR condition and 15 from 67 events in the TOR-only condition in which participants already had their eyes on road). According to a paired t-test, this difference in eyes-on-road-time was not statistically significant (see Table 7.3 and Figure 7.9). The maximum eyes-on-road time in the MR+TOR condition was 3.84 s, which means that all participants responded to the MR before the TOR, which was presented 7 s after the MR.

Concerning the eye-gaze behaviour during automated driving in between the zebra crossings, the average percentage of time with eyes on road across the participants for the MR+TOR and TOR-only conditions were 17.71% and 16.43% (SD = 13.98%, 14.05%), respectively, a difference that was not statistically significant between the two conditions (see Table 7.3 and Figure 7.10a). This finding indicates that participants were equivalently distracted in both conditions, as could be expected.

7.3.3 Take-over performance

Figure 7.8 shows drivers' braking actions in the situations where pedestrians were crossing the road and TORs were provided. It can be seen that, on average, participants applied slightly earlier braking, and reduced their speed earlier in the MR+TOR condition than in the TOR condition. Table 7.3 shows the corresponding descriptive statistics for the five take-over measures in the MR+TOR and TOR-only conditions, as well as pairwise comparisons between these conditions. The hands-on-wheel was 3.02 s faster and braking was 0.44 s faster in the MR+TOR condition than in the TOR-only condition. Thus, the results in Figure 7.7 and Table 7.2 indicate that the MRs effectively raised drivers' readiness to make the transition back to manual control of their vehicle. In the MR+TOR condition, the participants even put their hands on the steering wheel on average before the onset of the TOR. In Figure 7.9, the sequence of participants' responses is illustrated for eyes-on-road, hands-on-wheel, braking, and steering. The observed minimum TTC in the MR+TOR condition was 0.27 s longer than in TOR-only condition (consistent with the fact that participants braked earlier), indicating a safer response. However, the maximum deceleration was not significantly different between these two conditions (see Table 7.3, Figure 7.10b and Figure 7.10c).

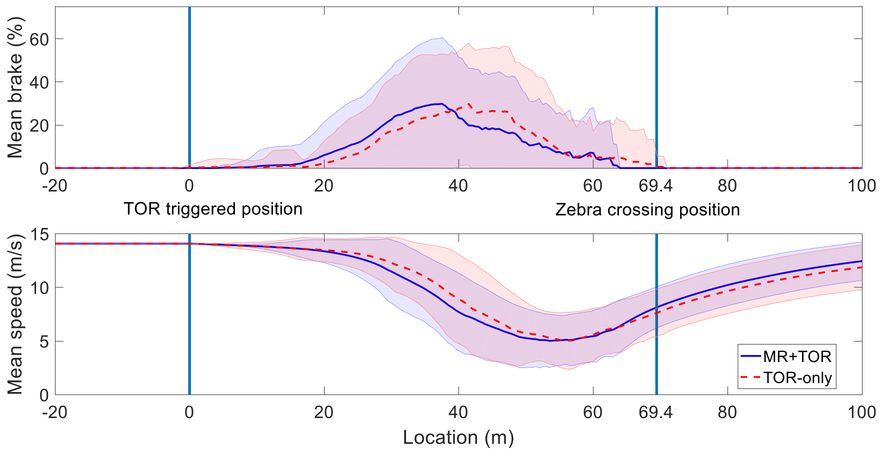

Figure 7.8: Means and standard deviations across events of the brake position and driving speed in the take-over scenarios in the MR+TOR and TOR-only conditions as a function of travelled distance. The vertical lines mark the start of the TOR (0 m) and the position of the zebra crossing (69.4 m). Note that these are averages, which means that these graphs cannot be used to make inferences about the behaviour of individual participants. For example, the minimum averaged speed in this graph is about 5 m/s, while the majority of the participants came to a full stop.

Table 7.3: Means and standard deviations of participants for gaze behaviour and take-over response times measures in the MR+TOR and TOR-only conditions, and pairwise comparisons between the two conditions.

		Eyes-on-road response time (s)	**Eyes-on-road percentage (%)**	**Hands-on-wheel time (s)**	**Brake initiation time (s)**	**Steer initiation time (s)**	**Maximum deceleration (m/s^2)**	**Minimum TTC (s)**
MR+TOR	M	1.85	17.71	-0.38	1.86	7.91	-8.42	2.83
	(SD)	(0.51)	(13.98)	(3.26)	(0.59)	(5.49)	(0.97)	(0.54)
TOR-only	M	1.76	16.43	2.64	2.30	8.72	-8.72	2.56
	(SD)	(0.73)	(14.05)	(1.88)	(0.61)	(4.32)	(1.00)	(0.72)
Paired t-test	t	1.45	0.75	-5.94	-4.53	-0.54	1.46	3.24
	df	28	33	37	37	29	37	37
	p	0.159	0.462	**<0.001**	**<0.001**	0.594	0.152	**0.003**
	r	0.44	0.75	0.35	0.50	0.086	0.16	0.70

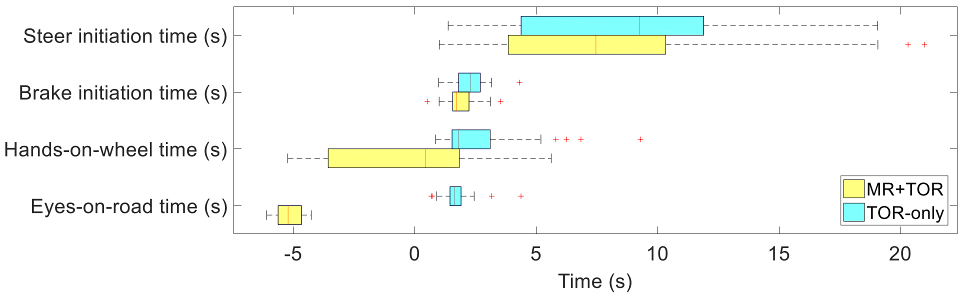

Figure 7.9: Box plots at the level of participants for eyes-on-road, hands-on-wheel, braking, and steering. The figure is created so that the temporal sequence of events is illustrated. The TOR is provided at 0 s, while the MR is provided at -7 s. The eyes-on-road time in the MR+TOR condition is the response to the MR; the other measures are all with respect to the TOR. Negative values indicate that the corresponding behaviour occurred before the TOR onset.

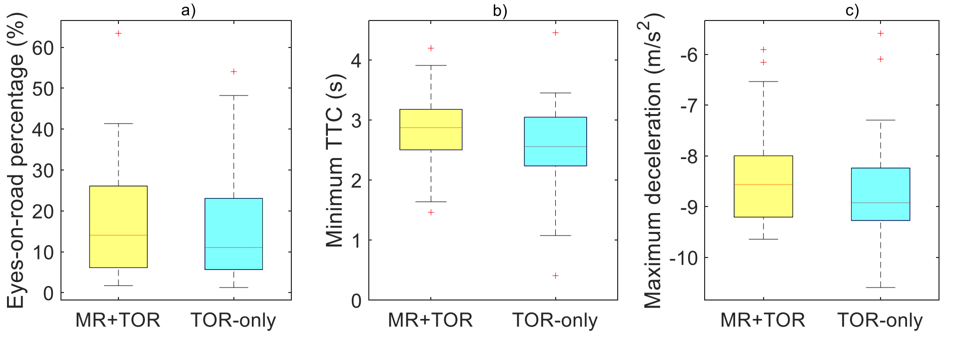

Figure 7.10: Boxplots at the level of participants for the a) percentage time eyes-on-road, b) minimum TTC, and c) maximum deceleration. Three participants who crashed (i.e., minimum TTC = 0 s) were not included in this figure.

7.3.4 Subjective evaluation

7.3.4.1 NASA-TLX

The overall workload is the average score of the six questions in NASA-TLX. There was a statistically significant difference in the scores of the MR+TOR ($M = 20.6$, $SD = 13.4$) and TOR-only ($M = 26.5$, $SD = 13.0$) conditions, $t(37)= -3.39$, $p = 0.002$, $r = 0.67$. The temporal demand, frustration, and effort items yielded significantly lower scores in the MR+TOR as compared to the TOR-only condition (Table 7.4).

Table 7.4: Means and standard deviations of the self-reported workload per condition.

		Overall workload (%)	Mental demand (%)	Physical demand (%)	Temporal demand (%)	Performance (%)	Frustration (%)	Effort (%)
MR+TOR	M (SD)	20.6 (13.4)	21.5 (20.5)	15.0 (14.2)	25.3 (22.3)	14.4 (17.7)	13.7 (19.3)	13.6 (13.7)
TOR-only	M (SD)	26.5 (13.0)	26.0 (21.2)	16.9 (16.1)	36.7 (28.0)	17.0 (19.3)	21.6 (25.7)	22.6 (19.6)
Paired t-test	t(37)	-3.39	-1.73	-0.90	-2.82	-0.89	-2.14	-3.16
	p	**0.002**	0.092	0.375	**0.008**	0.378	**0.039**	**0.003**
	r	0.67	0.70	0.62	0.54	0.52	0.52	0.49

Note. The scores on the items are from low (0%) to high (100%), except for the performance item, which is expressed from high (0%) to low (100%).

7.3.4.2 Usefulness and Satisfaction Scales

The mean usefulness score for the MR+TOR condition (M = 85.0, SD = 10.6) was significantly higher than for TOR-only condition (M= 79.1, SD= 11.3), t(37) = 3.02, p = 0.005, r = 0.39. Similarly, participants were more satisfied with the system in the MR+TOR condition (M = 88.5, SD = 12.3) compared to the TOR-only condition (M = 80.6, SD = 17.1), t(37)= 3.42, p = 0.002, r = 0.57.

7.3.4.3 Usability

The usability score (average of the five usability items) was not significantly different between the MR+TOR condition (M = 97.0, SD = 5.4) and the TOR-only condition (M = 96.1, SD = 5.8), t(37) = 1.25, p = 0.220, r = 0.64.

7.3.4.4 Trust

All trust-related scores for the MR+TOR and TOR-only conditions are shown in Table 7.5. All items showed higher trust in the MR+TOR condition, especially for harm, confidence and security. Additionally, when asked about their preference between the two systems, 31 out of 38 participants preferred the MR+TOR to the TOR-only system.

Table 7.5: Means and standard deviations of participants for the responses to the trust questionnaire, and results of paired t-tests between conditions

		Mistrust	Harm	Suspicion	Confidence	Security
MR+TOR	M (SD)	30.6 (34.6)	18.4 (23.2)	20.2 (27.2)	84.2 (18.2)	84.2 (15.0)
TOR-only	M (SD)	35.5 (34.5)	28.5 (25.7)	25.9 (27.3)	75.0 (23.8)	73.7 (21.4)
Paired t-test	t	-0.82	-3.38	-1.68	3.39	4.26
	df	36	37	37	37	37
	p	0.419	**0.002**	0.102	**0.002**	**<0.001**
	r	0.54	0.72	0.70	0.71	0.71

7.3.5 Monitoring request without take-over request

The third condition ‘MR-only’, of which the results were not provided above, was included at the end of the experiment. Because this condition had a different design, the results are discussed separately in the present section. The MR-only condition was included to study whether participants relied on the TOR to follow the MR and to see if participants would still respond to a critical situation if no TOR was provided.

From the 38 participants, three crashed into the pedestrians in the last scenario. Participants' eyes were on the road and hands on the wheel during all three crashes, but participants did not intervene (see also Victor et al., 2018). In a post-experiment interview, all three participants reported their expectation and reliance on the TOR. An overview of the eye movement and braking actions in the pedestrians crossing scenarios in MR+TOR and TOR-only conditions is provided in Figure 7.11. It shows that, on average, participants applied later and harder braking in the MR-only condition than in the MR+TOR condition. Moreover, it is clear that people in the MR-only condition focused on the road rather than on the instrument cluster, presumably because no TOR was shown on the instrument cluster.

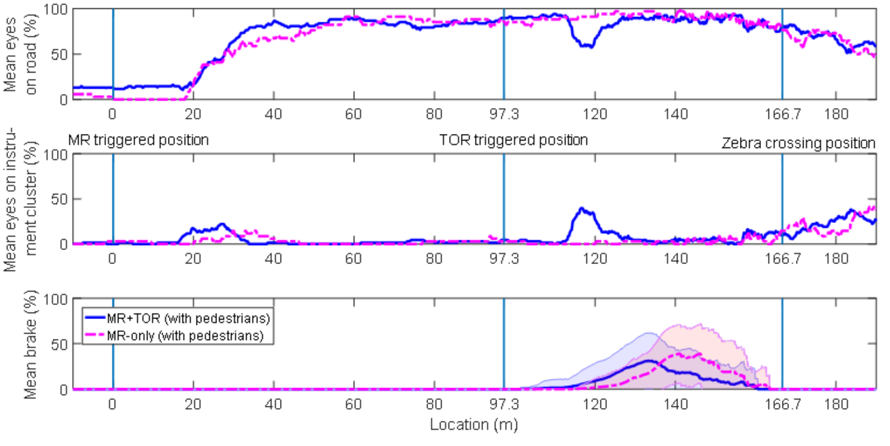

Figure 7.11: Participants' mean visual attention allocation across events on the windshield (upper plot) and instrument cluster (middle plot) and means and standard deviations across events of the brake position (lower plot) in the pedestrians crossing scenarios in the MR+TOR and MR-only conditions as a function of travelled distance. Three vertical lines from left to right are the locations of the MR (triggered position = 0 m), TOR (triggered position = 97.3 m), and zebra crossing (166.7 m).

We also compared three performance measures (maximum deceleration, brake initiation time, minimum TTC) in the pedestrian crossing scenarios between the MR+TOR and MR-only conditions (Table 7.6). The three collisions were not included in the comparison because the brakes were not applied. We assessed learning effects by comparing the two scenarios with pedestrians within the MR+TOR condition. Next, we tested whether the learning trend was counteracted by the lack of a TOR, by comparing the MR-only event ('no TOR') with the second MR+TOR event.

As shown in Table 7.6 and Table 7.7, participants braked significantly earlier and with less deceleration after the second TOR compared to the first TOR in the MR+TOR condition. However, this learning effect did not continue into the MR-only condition: In the MR-only condition, participants braked significantly later and harder compared to the second TOR of the MR+TOR condition. No statistically significant difference of minimum TTC was observed in the two pedestrian-crossing events of the MR+TOR condition. However, in the MR-only condition, the minimum TTC was significantly shorter compared to the first and second TOR of the MR+TOR condition. Summarizing, participants braked later in the MR-only condition (TOR only) as compared to MR+TOR condition, despite an expected learning effect in the opposite direction.

Table 7.6: Means and standard deviations of participants for the braking measures in the MR+TOR and MR-only conditions

	Maximum deceleration (m/s²)	Brake initiation time (s)	Minimum TTC (s)
First TOR (MR+TOR condition)	-8.84 (0.93)	2.06 (0.71)	2.75 (0.66)
Second TOR (MR+TOR condition)	-8.00 (1.45)	1.82 (0.63)	2.91 (0.60)
No TOR (MR-only condition)	-9.10 (0.64)	2.37 (0.55)	1.98 (0.82)

Table 7.7: Results of paired t-tests between performance measures regarding the first TOR in the MR+TOR condition, the second TOR in the MR+TOR condition, and no TOR in the MR-only condition.

	Maximum deceleration (m/s²)				Brake initiation time (m)				Minimum TTC (s)			
	Second TOR (MR+TOR condition)		No TOR (MR-only condition)		Second TOR (MR+TOR condition)		No TOR (MR-only condition)		Second TOR (MR+TOR condition)		No TOR (MR-only condition)	
	t(37)	p	t(34)	p	t(37)	p	t(34)	p	t(37)	p	t(34)	p
First TOR (MR+TOR condition)	-3.52	0.001	1.33	0.192	2.36	0.023	-2.96	0.006	-1.44	0.159	6.28	<0.001
Second TOR (MR+TOR condition)			4.94	<0.001			-6.91	<0.001			8.33	<0.001

7.3.6 Compliance with MRs

7.3.6.1 Probability of preparatory behaviour

All participants responded to the MR by looking to the road. Hence, the ‘eyes’ probability was 1 for each MR block. Figure 7.12 shows the percentages of participants per block in which a hand (left) or foot (right) preparatory behaviour occurred. Results indicate an increase in hand and foot preparation in *After TO* blocks as compared to the previous block. If the participant had experienced no TOR at all, the probability of preparation was overall low and/or showed a decreasing trend (red circular markers).

Regarding hand preparations in the third block: From the three participants who had experienced two take-overs before, all three were prepared (black diamond marker), and from the six participants who had experienced no take-overs before, only three were prepared (red circular marker). Similarly, regarding foot preparations in the third block: From the four participants who had experienced two take-overs before, all four were prepared (black diamond marker), and from the four participants who had experienced no take-overs before, none were prepared (red circular marker).

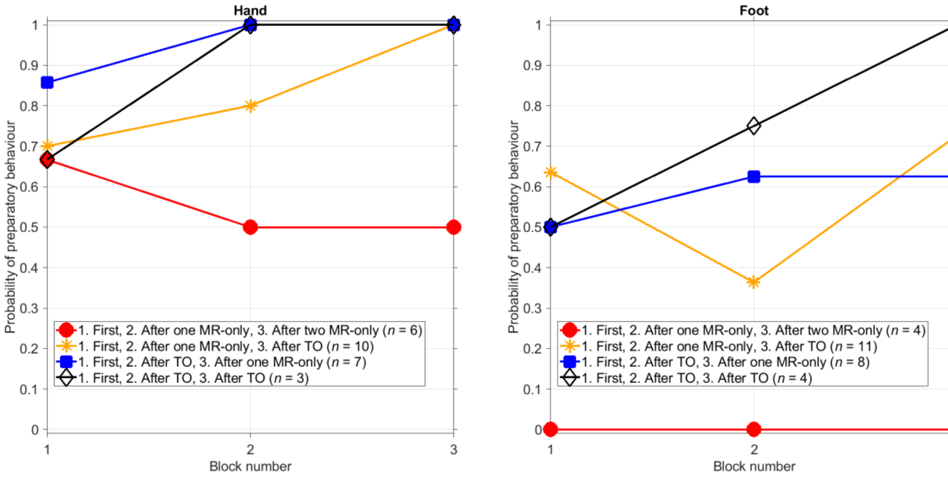

Figure 7.12: Probability of hand (left) and foot (right) preparatory behaviour for the first three blocks.

7.3.6.2 Latency of Preparatory Behaviour

Averaged over all five MR blocks, participants started looking to the road on average 0.70 s (SD = 0.38) after the MR. The start of hand and feet movement (if available) occurred on average 2.13 s (SD = 1.09) and 3.17 s (SD = 1.55) after the MR, respectively. These effects are illustrated in Figure 7.13. Note that all response time data in the analysis of driver compliance were obtained from manual video annotations. Therefore, the mean eyes-on-road times reported in this section were different from those reported in Section 7.3.3 based on SmartEye eye-tracking data.

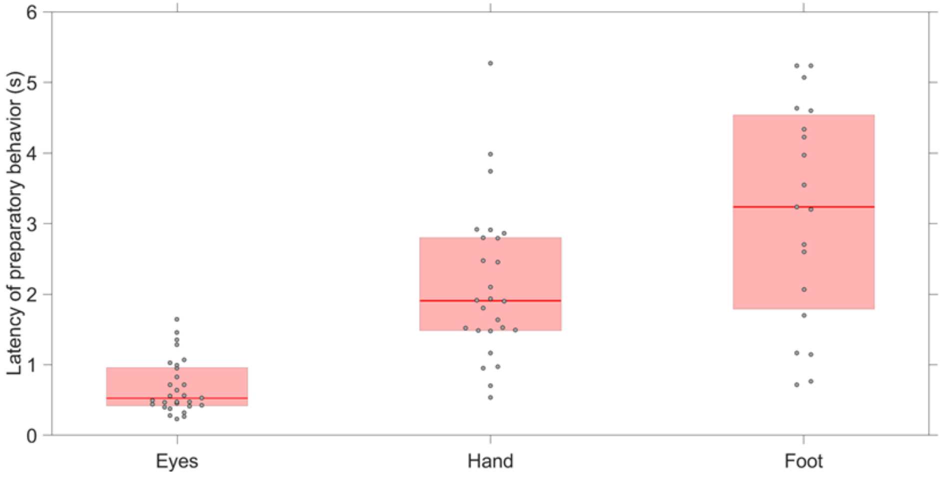

Figure 7.13: Latency of participants' preparations for Eyes (29 participants based on 115 observations), Hand (26 participants based on 87 observations), Foot (19 participants based on 46 observations)

7.3.6.3 Amplitude of Preparatory Behaviour

Figure 7.14 shows the means of hand and foot preparation levels. Results support the above observations that the mean level of preparation showed an increasing trend in the case of After TO blocks.

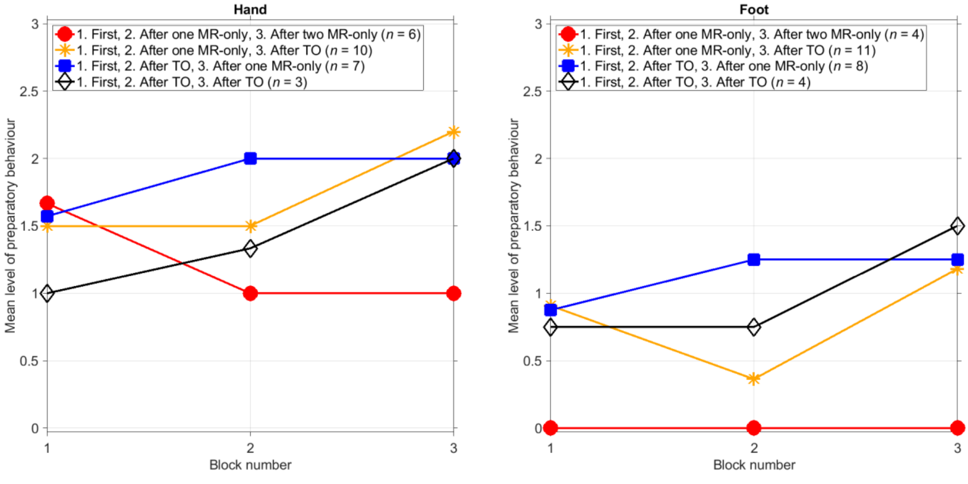

Figure 7.14: Mean level of hand (left) and foot (right) preparation for the four MR block categories.

7.3.6.4 Level of Preparation and Subsequent Take-Over Performance

Table 7.8 shows the means and standard deviations of the take-over performance measures per level of hand and foot preparation. A tendency can be observed that take-over performance improved with higher levels of preparation, where better take-over performance is characterized by a shorter take-over time, a longer minimum TTC, and a lower maximum deceleration. Also, learning effects were observed from the first take-over event to the second, in line with Lu et al. (2019). It is worth noting that a larger number of participants showed the highest level of preparation before the second take-over event as compared to the first event. The trends of preparation level and take-over attempt are illustrated in Figure 7.15.

Table 7.8: Means with standard deviations in parentheses of take-over response time, minimum TTC, and maximum deceleration for each level of hand and foot preparation.

Hand preparation	**Level 0**	**Level 1**	**Level 2**	**Level 3**
First take-over	***n* = 6**	***n* = 7**	***n* = 7**	***n* = 4**
Take-over time (s)	2.49 (0.78)	1.94 (0.79)	2.10 (0.64)	1.89 (0.30)
minTTC (s)	2.45 (0.75)	2.53 (0.52)	2.64 (0.60)	2.76 (0.51)
maxDEC (m/s^2)	9.49 (0.57)	9.36 (0.27)	8.47 (1.05)	8.79 (0.86)
Second take-over	***n* = 4**	***n* = 7**	***n* = 8**	***n* = 7**
Take-over time (s)	1.90 (0.60)	1.97 (0.80)	2.07 (0.68)	1.53 (0.41)

minTTC (s)	2.98 (0.57)	2.81 (0.70)	2.55 (0.70)	2.93 (0.45)
maxDEC (m/s^2)	7.93 (1.33)	8.64 (1.00)	8.38 (1.66)	7.42 (1.81)
Foot preparation	**Level 0**	**Level 1**	**Level 2**	
First take-over	***n* = 16**	***n* = 6**	***n* = 4**	
Take-over time (s)	2.03 (0.82)	2.01 (0.45)	1.64 (0.39)	
minTTC (s)	2.73 (0.79)	2.72 (0.37)	2.94 (0.39)	
maxDEC (m/s^2)	9.14 (0.51)	8.94 (0.56)	9.26 (0.01)	
Second take-over	***n* = 12**	***n* = 7**	***n* = 9**	
Take-over time (s)	2.00 (0.59)	1.66 (0.42)	1.20 (0.37)	
minTTC (s)	2.83 (0.60)	2.95 (0.47)	3.16 (0.51)	
maxDEC (m/s^2)	8.27 (0.96)	7.55 (1.88)	7.56 (1.62)	

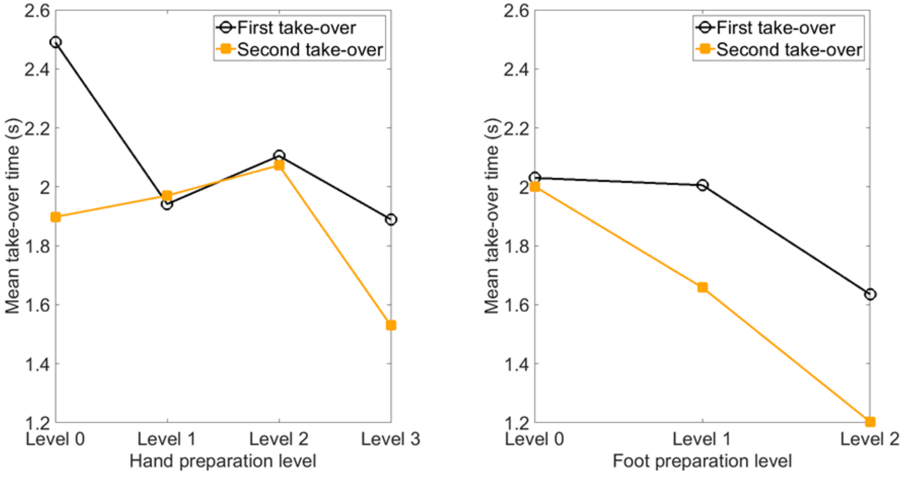

Figure 7.15: Association between hand and foot preparation levels and take-over time. Standard deviations are shown in Table 7.8.

7.4 Discussion

7.4.1 Main findings

The main aim of this study was to investigate 1) whether drivers are responsive to MRs by redirecting their attention to the road, 2) whether drivers unnecessarily take over control when no action is needed, and 3) whether drivers have a shorter takeover time when being forewarned by the MR as compared to when receiving only a TOR. Accordingly, a systematic comparison of participants' behaviours was made between an MR + TOR system and a traditional TOR-only system. The results indicate that participants showed strong compliance with the MRs: Participants were responsive to the MR by looking at the road, and several participants placed their hands on the steering wheel without specifically being asked to do so. These behaviours indicate that drivers were preparing themselves for a possible take-over. With their eyes on the road and their hands already on the wheel, the drivers responded faster to TORs in the MR + TOR condition in comparison to the TOR-only condition. The longer minimum TTC values measured in the MR + TOR condition as compared to the TOR-only condition indicate that the MRs helped improve safety. Although the observed improvements (e.g., 0.44 s faster brake response time) may seem modest on an absolute scale, we argue that they can translate into large safety benefits. For example, if decelerating with 8 m/s2, 0.44 s longer braking implies an additional speed reduction of 13 km/h. This speed difference can be expected to yield substantial improvements in the probability of surviving a crash (Joksch, 1993).

Additionally, we found only one unnecessary braking action when no pedestrians were crossing the road, which means the MRs hardly caused unnecessary take-overs when no action was needed. We also found that drivers experienced lower subjective workload, higher acceptance (usefulness and satisfaction), and higher trust for the MR + TOR condition as compared to the TOR-only condition, whereas there were no statistically significant differences in experienced usability. In other words, MRs not only yielded positive effects on behaviour but were generally also experienced as positive. Finally, the presentation of MRs did not change drivers' attention allocation during the automated driving periods, indicating that drivers still felt comfortable to perform the non-driving task in between MRs.

Summarising, the MR concept worked as intended: It permitted drivers to be engaged in a non-driving task (as in a highly automated driving system), and still ensured that participants were attentive and prepared for an upcoming event (as in a partially automated driving system). Thus, our findings show that MRs promote a gradual transition between being disengaged from the driving task and actually taking over control. Put differently, the MRs effectively exploit the idea that automated driving can independently involve driver monitoring transitions and control transitions (Lu et al., 2016). Our results align with previous studies (Cohen-Lazry et al., 2017; Dziennus et al., 2016; Gold et al., 2013; Helldin et al., 2013; Yang et al., 2017), which have shown that MRs and other types of uncertainty indicators stimulate driver to allocate attention to the road when encountering an unpredictable driving environment, in turn yielding improved responses in critical situations.

7.4.2 Driver Compliance with MRs

In addition, we investigated how drivers complied with MRs, how the level of compliance changed with experience within one test session, and how the level of compliance associated with subsequent take-over performance. Compliance was measured by the three indices adapted from Breznitz (1984): probability, latency, and amplitude of eye, hand, and foot preparatory behaviour, retrieved from manual video observation.

The results indicated high overall compliance with MR. Participants looked up onto the road within a short time in all cases, and moved their hands to be better prepared for a possible take-over (e.g., putting down the iPad) in the majority of the cases. In several cases, participants also moved their feet closer to the pedal, but the probability of feet movements was smaller, and the associated latency was higher, than hand preparatory behaviour.

We found a higher preparation probability in response to MRs after a take-over event as compared to MRs after two consecutive MRs without take-over event, in line with the statements of Breznitz (1984) that threat cancellation reduces protective behaviour, whereas hit alarms increase compliance. We observed that after experiencing one or two MRs without critical event, a few participants did not look up as soon as possible, but continued with the non-driving task for a short time. Some participants monitored the road only shortly, and continued with the non-driving task even before the MR was dismissed. Such potentially risky behaviour may increase as more consecutive MRs without event are experienced in a prolonged drive. Also, drivers may develop alarm fatigue (Cvach, 2012) by excessive ‘unnecessary’ MRs, and turn off the notification system.

Furthermore, our findings suggest a substantial influence of preparation behaviour on take-over times: when monitoring with a hand on the wheel or with a foot hovering above the pedal, drivers responded faster to the TOR as compared to without any hand or foot preparation action. This is possibly due to a reduction of hand/foot travelling distance (Zhang, Wilschut, Willemsen, & Martens, 2019).

7.4.3 Reliance on the TOR

In the final trial of our experiment, we examined whether people over-rely on the TOR, despite the fact that they have received an MR prompting them to monitor the driving environment. When drivers who were previously exposed to perfectly reliable TORs were provided with only an MR, they showed worse takeover performance as compared to the MR + TOR condition. Three out of 38 participants collided with the pedestrians, whereas the other participants showed higher mean response times, more severe braking, and a smaller minimum TTC as compared to the MR + TOR condition. These effects occurred despite the fact that they were looking at the driving environment and were told that the TOR would be available only if a critical event was detected successfully. This over-reliance may have been caused by the fact that participants were conditioned to respond to the TORs, not to the hazards (i.e., pedestrians) themselves. It is also possible that participants had built inappropriately high trust in the TORs because all preceding pedestrian crossing events came with a TOR. Lee and See (2004) argued that human trust needs to be calibrated according to the context and characteristics of automation. Further research could investigate how to prevent over-reliance on TORs. One idea is to examine whether a variable ratio of the number of TORs over the number of MRs could affect driver trust levels and their responses to the MR.

7.4.4 Limitations

This study has several limitations. First, we presented pedestrian crossing scenarios only, which may have contributed to reduced response times due to familiarity. In future research, a larger variety of scenarios could be tested, including time critical situations and voluntary transitions such as merging or exiting the highway. Future research might also use a between-subjects rather than within-subject design to prevent carry-over effects. However, it is cautioned that between-subjects designs require a substantially larger sample size in order to maintain adequate statistical power. Second, this study used fixed time budgets for monitoring (i.e., 12 s before the collision) and taking over (i.e., 5 s before the collision), which may have led to specific expectations about the timing of taking back control. The time budget between an MR and a TOR could be further investigated. If an MR is provided early, drivers may lose attention again, whereas if an MR is provided late, there may be insufficient time to prepare for taking over. Third, drivers’ behaviour was only observed within short experimental sessions. For the assessment of driver compliance, the maximum number of successive cancellations was two. It is likely that a more severe reduction in preparatory behaviour would occur if more MR blocks were implemented. Moreover, as pointed out in a review by Green (2000), expectancy is an important determinant of brake response times. In our experiment, there were no true surprises. That is, the participants were probably expecting at least one take-over event in the entire session. If no event has occurred yet, each transition from one MR to another implies that the take-over event is approaching: Successive MRs without TOR implied greater proximity of danger, which may counteract the decrease in compliance (cf. Chapter 5 in Breznitz, 1984).

Finally, simulator fidelity may be an issue. The absence of physical motion cues may have an effect on how drivers brake (Boer, Yamamura, Kuge, & Girshick, 2000; Siegler, Reymond, Kemeny, & Berthoz, 2001) and may have reduced drivers' awareness of the automation mode (Cramer, Siedersberger, & Bengler, 2017). It is also possible that the presentation of virtual hazards, rather than real hazards, has reinforced the ''wait and see" behaviour in the MR-only condition. In addition, participants in an experimental setting tend to 'behave well'; preparatory behaviour may be less in real life settings. In future studies, various reliabilities of TOR and MR should be investigated to reach conclusions that are more credible.

7.5 Conclusion

The observed effects of MRs are promising. The MRs directed the drivers' attention to the road and improved their response to a subsequent TOR. Furthermore, the MR + TOR was positively evaluated for workload, usefulness, and satisfaction. We argue that automated driving systems that provide only TORs are not exploiting the richness of sensory information, both of the human and the automation sensor suite. The concept of MR makes use of the fact that automated driving systems have variable certainty about the situation. In our case, we demonstrated the MR concept when the car approaches a zebra crossing, a part of the road entailing a high likelihood that the driver has to take over control.

The simulated MR is realistic in terms of automated driving technology. Differential GPS, HD maps, and traffic data could be used as inputs to the automated driving system to provide an MR when approaching a potentially critical road section, unlike camera and lidar, which are constrained by their detection ranges. However, we caution that the provision of MRs does not guarantee safety. We observed a situation-dependent change in the compliance level, which was associated with driving performance during a subsequent take-over event. That is, the cry-wolf effects may be a concern in the use of MR. We also showed that when the automated driving system fails to detect a hazard and accordingly fails to provide a TOR, a proportion of drivers still crashed. Future research should be focused on measures to counteract the cry-wolf effect such as training and education (Breznitz, 1984; Zabyshny & Ragland, 2003), and conducted on the topic of over-reliance on take-over requests and individual differences in the use of automated vehicles.

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8. Conclusions, discussion and implication for practice

The aim of this thesis was to investigate car and truck drivers' behaviour and performance when resuming manual control back from automated driving, in order to provide input for designing safe and smooth take-over control strategies. The literature and empirical studies addressed the research questions defined in this thesis.

RQ1: What factors influence driver response times in taking back control from automated to manual driving

To answer this research question, a comprehensive meta-analysis was conducted to systematically synthesize the findings of 129 studies that measured take-over response times in a wide range of experimental conditions related to the driver, the vehicle, the take-over situation, and the experimental set-up. Results clearly showed some systematic effects on driver take-over time. Most prominent factors were:

1) Urgency of the take-over situation:
   The mean take-over time was substantially lower when the take-over situation was more urgent (with a shorter time budget available).
2) Non-driving task performed during driving automation
   Mean take-over times were substantially higher when the driver was holding an object in the hands or resting with the eyes closed. Performing a visually demanding non-driving task moderately increased the mean take-over response time.
3) Modality used for the take-over request:
   The mean take-over time was substantially lower when an auditory and/or vibrotactile take-over request was provided compared to a visual-only or no take-over request.
4) Experience and familiarization:
   The mean take-over time was substantially lower when the driver had prior experience with the take-over situation.

5) Anticipation:
   Being able to anticipate the take-over request from task-related or environmental cues reduced mean take-over response times.
6) Traffic situation:
   The mean take-over time was higher when other road users needed to be taken into consideration during the take-over process (e.g., participants had to take over control while driving in the middle lane, while the right/left lane contained traffic.)

Other examined factors, including drivers' mean age, whether the non-driving task demand is auditory or cognitive, whether the take-over request was directional or with peripheral visual stimuli, duration of the driving automation task, the complexity of take-over response, and the fidelity of the driving simulator, only showed minor or inconsistent influence on mean take-over times.

Besides findings of the meta-analysis, the empirical studies in this thesis provided additional insight into driver take-over times and its influencing factors. In the platooning studies, the total take-over time was broken down into two stages:

- Perception response time (to perceive and understand the take-over request) and
- Hand movement response time (to replace hands back on the steering wheel).

It was found that in most cases the hand-movement response time was significantly higher than the perception response time, suggesting movement response time as a dominant component of the total take-over time. Therefore, factors influencing driver motoric take-over process, such as non-driving posture and activities performed when resuming an optimal manual driving position, would substantially influence take-over response times. It was also found that car drivers took over significantly faster than professional truck drivers after using a hand-held tablet, which suggested that either driver type or vehicle type potentially is an influencing factor of take-over times.

This thesis also explored effects of two innovative driver assistant systems on take-over response times. Chapter 6 explored the possibility to overcome the restricted visual anticipation of short-distance platooning in trucks by implementing a see-through lead truck. Despite increasing eyes-on-road time during platooning, providing truck drivers with front view projection did not affect their take-over times in a critical situation compared to not using such technology. Chapter 7 investigated the effect of a monitoring request on driver take-over performance. Provided with both monitoring requests and take-over requests, drivers already regained certain level of mental and motor readiness before an actual take-over was required, and took over significantly faster compared to using a system that only provided take-over requests. This study further suggested that reliance with take-over requests and compliance with MRs could influence drive take-over times.

An overview of factors influencing take-over response times is depicted in Figure 8.1. These factors are mainly based on the meta-analysis that drew relatively more credible conclusions based on at least four studies. Other potentially influencing factors that were not included in the meta-analysis (i.e., too few studies investigated these factors by far) were also suggested based on findings of the empirical studies and previous literature.

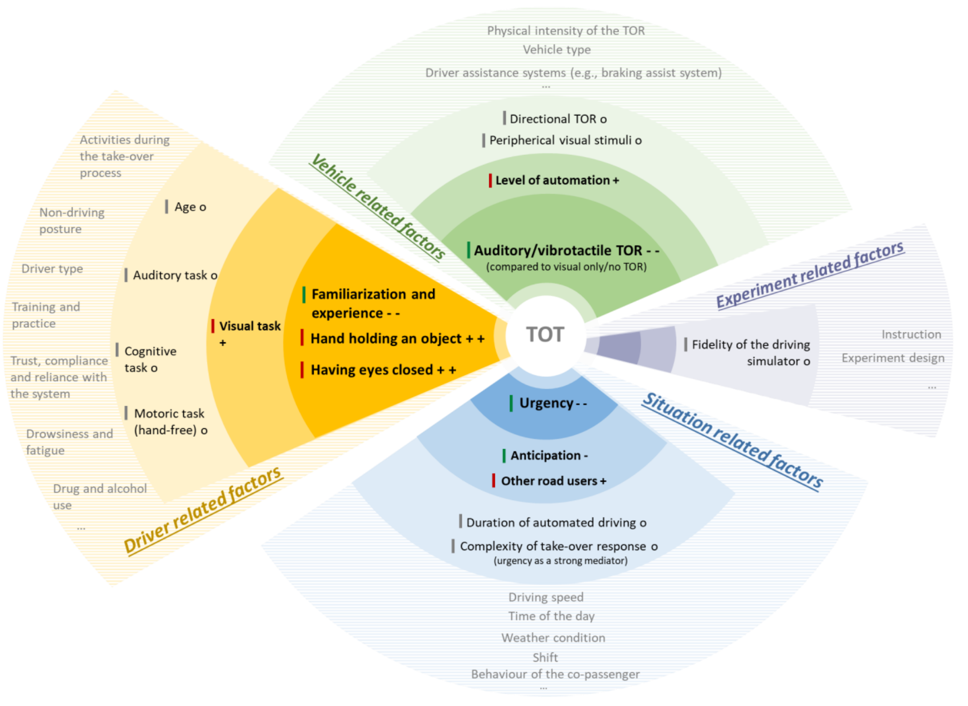

Figure 8.1: Overview of factors influencing driver take-over response times (TOT) clustered in four categories: driver related, vehicle relate, situation related, and experiment related. Factors in the three inner layers were examined in the meta-analysis based on at least four studies, so with multiple replicated results. Factors in the innermost layer and the second inner layer have strong effects (marked with two signs) and moderate effects (marked with one sign) on take-over times, respectively. The red bar and the plus sign indicate that the presence of the corresponding factor increases take-over times, while the green bar and the minus sign indicate the opposite effect direction. The factors marked with a circle (in the third inner layer) have minor or inconsistent effects on take-over times. Factors in the outermost layer (in grey) were examples of other potentially influencing factors suggested in the empirical studies and previous literature, which were not included in the meta-analysis because there were no 4 studies available.

- **RQ2: How do professional truck drivers and car drivers perform when decoupling from highly automated platoons in normal, non-critical situations under the influence of various task conditions?**

The meta-review showed that hardly any studies were performed in a platooning context but rather with stand-alone automation. This thesis filled in this gap and specifically studied professional truck drivers' and car drivers' take-over performance when decoupling from an automated platoon, and how this can be influenced by four representative task conditions, namely monitoring (without non-driving tasks), using a handheld tablet, using a mounted tablet, and resting with eyes closed. The performance metrices concerned take-over response times, response to a brake event (immediately after the transition), and manual driving performance subsequent to the transition.

When required to take over control without time restrictions while platooning, drivers depicted large variation in response times ranging from 1.6 s to 13.3 s (combining all trials performed in the three empirical studies). Drivers took substantially more time to take over control after using a hand-held tablet or resting with eyes closed compared to monitoring the road. Performing a standardized visual-motoric task on a mounted tablet while platooning also generated a higher take-over time compared to the monitoring condition, but of smaller magnitude than holding the tablet in the hands. It was also found that car drivers in platoons took over faster than truck drivers in platoons due to a lower hand movement response time. Video recordings revealed that a number of truck drivers encountered additional barriers in the motoric take-over process such as having to switch reading glasses or taking extra time to shut down the tablet screen.

In response to the decelerating lead truck immediately after the control transition, all drivers could brake in time and avoid a collision after monitoring the road or using a tablet, while one crash occurred to a truck driver in the Eyes-closed condition due to delayed response. These findings suggest that in most cases drivers were ready for moderately complex driving situations after resuming control in non-critical scenarios after platooning with relatively low time headways. Impairing effects of using a tablet on post-transition brake response were only found for car drivers, while truck drivers did not depict differences in performance between task conditions. Significant differences between driver groups were suggested, in that professional truck drivers responded faster and braked more smoothly compared to car drivers. Truck drivers showed overall more robust and better brake responses, possibly due to their higher level of training and expertise than average car drivers.

In the trials without brake events, drivers' longitudinal and lateral manual driving performance were assessed after the transition to gain insight into carry-over effects of automated platooning involving small inter-vehicular gaps. Both car and truck drivers reduced the speed immediately after the control transition to increase following distances (time headways), but still drove with reduced time headways one minute after decoupling compared to their baseline time headway in the manual driving conditions. This implied that carry-over effects of platooning may last for several minutes after the control transition. Such effects appeared to be more profound after monitoring the lead vehicle while platooning, especially for truck drivers.

Impact of platooning on drivers' lateral control performance was only marginally present for truck drivers for the first 10 s after the control transition, in specific conditions. The first truck platooning study showed increased mean SDLP after having used a handheld tablet during platooning. In the second truck platooning study such effect was only found in the monitoring condition, but not in the mounted tablet condition or the eyes-closed condition. The inconsistent findings call for more studies for valid conclusions.

- **RQ3: Could a monitoring request help driver respond more adequately with take-over performance in critical take-over situations?**

In Chapter 7, a design solution was proposed and evaluated that aims to bridge the gap between automated with a driver out of the loop and completely manual driving. The proposed 'monitoring request' is designed to stimulate a dynamic allocation of monitoring tasks to the human driver and the automation system according to the uncertainty of the road segment. Drivers could take their eyes off the road and engage in non-driving tasks in relatively predictable and safe driving situations, and would be requested to monitor the road upon approaching an uncertain road segment for which the vehicle could not reliably predict whether critical take-over events are likely to occur. The system also provides a take-over request upon detection of an actual critical event.

Results of the study in general showed positive effects of the monitoring request. After receiving a monitoring request, all drivers paused the undergoing non-driving tasks on a hand-held tablet and looked up on the road. Several drivers also resumed motor readiness by replacing hands on the wheel and hovering the feet above the pedal. These preparatory behaviours led to better take-over performance when a critical event actually occurred compared to the condition that only provided take-over requests, in terms of a shorter response time to the take-over request and a higher minimum time to collision. Drivers also expressed more positive subjective ratings regarding workload, trust, and acceptance after experiencing the innovative system compared to the system that only issued take-over requests. Furthermore, the presence of monitoring request did not affect drivers' eye-gaze behaviour during automated driving (i.e., in between the uncertain areas without system issued requests). In both conditions, drivers were equivalently distracted by the non-driving task and spent approximately 17% time looking on the road.

This study also suggested that the system providing both monitoring requests and take-over requests may induce potential risks. After experiencing the perfectly functioning system, drivers showed significantly worse take-over performance when the system only issued a monitoring request but failed to issue a take-over request upon a critical event, compare to the conditions in which they did receive a take-over request. Drivers appeared to over-rely on the TORs and seemed to have developed a "wait and see" attitude. In addition, because only a small portion out of all monitoring requests required an actual driver take-over, drivers tend to reduce motoric preparatory behaviours after experiencing successive monitoring requests that did not require an actual takeover, and took over more slowly if an actual take-over event occurred under such circumstances. These findings suggest that overreliance on the take-over request and the cry-wolf effect could be concerns in the use of such system, and measures should be applied to stimulate proper trust calibration.

- **RQ4: What explains variability in take-over times? Is an adaptive approach (tuned to a specific driver) a feasible solution to increasing safe and smooth transitions to manual driving?**

Besides focusing on mean take-over times, this thesis made efforts to understand within-group variability. The meta-analysis showed a strong positive correlation between mean take-over times and their standard deviations. This means that factors generate high mean take-over times would also generate large variability between drivers. The empirical studies especially addressed that the variation in the motoric take-over process was a main source for the variation in total take-over times. Very slow take-over responses were often associated with complex and random motoric activities when resuming motor readiness, such as looking for reading glasses, having difficulties adjusting seat position, double-checking if iPad was shut properly, putting on shoes that were taken off during automated driving, and stretching arms and necks. Large variation in drivers' perception time was also observed in the Eyes-closed condition. While some drivers could immediately respond to the take-over request, a few drivers seemed to have fallen asleep when the TOR was issued and only responded several seconds later. This situation generated the highest take-over response times measured in the empirical studies (>8.6 s, outside the 95th percentile).

The discussions above infer that dynamically changing driver states (e.g., task condition, posture, and mental states) and driving situation predominantly determine the driver's capability to take over control safely at a specific moment, while the driver's inherent characteristics, such as age, gender, and personality, only play a minor role. Therefore, a driving automation system that can adapt to individual drivers' states has potential to increase driving safety at intermediate development phases, where the driver would be allowed to perform various non-driving tasks, but is still expected to resume control when requested. For example, upon detection of insufficient driver states, the system could provide pre-warnings to advise the driver away from undesired NDTs, take precautions such as increasing headways to the front vehicle, and allow a longer time budget if a take-over is actually required. However, designers should foresee the limit in providing precise estimations of a specific drivers' take-over readiness, and exercise caution when designing and implementing adaptive automation systems.

One of the first issues would be that by far only a limited number of determinants of take-over times have been identified, merely based on empirical studies in strictly controlled environment. More factors are to be studied in naturalistic driving conditions for a holistic picture, which may require enormous efforts. Furthermore, several substantial determinants of take-over times are not observable and extremely difficult to predict (if not impossible), such as familiarization and expectation with a specific take-over situation, and very importantly, what the driver would actually do during the take-over process. One example is that a participant forgot where he had put his spectacles and searched for several seconds before taking over control. It has to be kept in mind that drivers are most vulnerable in these unpredictable outlier cases, which would occur more often when drivers are less restrained during automated driving. In addition, as the driver learns safe usage of the automation system and calibrates trust predominantly from long-term on-road experiences (Lin, Ma, & Zhang, 2017; Walker, Boelhouwer, Alkim, Verwey, & Martens, 2018), adaptive systems may be unpredictable and confusing for the driver if the set of criteria triggering changes is not transparent and comprehensive (e. g., no specific take-over time budgets). This may hinder the process of establishing a correct mental model and induces potential risks (cf. Billings & Woods, 1994).

The discussion above indicated that to precisely tune to each individual driver would be a rather unrealistic goal. To compensate for the potential limit of adaptive driving automation systems, designers could work on accurate estimations of the system's capabilities and the complexity of the driving environment, and adjust the available functionalities and HMI. If effectively informed about the system status, the drivers would regulate their states (e.g., adjusting non-driving task conditions and non-driving postures) before an actual takeover event occurs. This approach is related to the idea illustrated in Chapter 7, in which drivers established higher levels of mental and motor readiness after receiving a monitoring request (MR) that communicated the situation uncertainty, and exhibited good take-over performance when critical events actually occurred. Also, what the driver is allowed to do could be restricted based on the capability of the car to handle the specific circumstances it drives in. This could also be monitored, as is currently also discussed within international committees such as EuroNCAP, UN-ECE and ISO (SC39 WG8). Interesting aspect here is that the entire system is not aimed at automating as much as possible, but at offering automation when it is reliable, and taking precautions of this is not the case, using the human capabilities without providing a task that does not fit (e.g. continuous monitoring). It seems that driver monitoring systems are expected to be more capable of identifying if a driver's state is in line with minimum requirements. This means that even if a driver is estimated to be in a sufficient functional state (e.g., monitoring with hands on the wheel), (s)he might also fail in takeover due to unobservable and unpredictable factors, so a fallback option or emergency procedure should be available regardless of a driver's estimated state.

8.1 Implications for practice

Based on the findings of this thesis, several recommendations can be provided for researchers, industry and policy-makers towards safer transitions of control from automated driving to manual control. They are listed and explained below.

Regaining motor readiness plays a substantial role in the take-over process

This thesis pointed to the substantial influence of driver motoric take-over process on total take-over response times. If a fast take-over response may be requested (e.g., with a time budget shorter than 7 s), the driver should not engage in non-driving tasks involving severe biomechanical distractions, such as holding an object in the hand(s) or out of the driving position. Performing tasks on a mounted device close to the steering wheel would be more recommendable. In addition, the driver's non-driving postures and seating positions should be regulated to avoid undesired delay in takeover. The cabin interior elements could also be designed to regulate driver behaviours according to different automation modes and driver's use scenarios. For example, when driving in a complex area that requires driver monitoring, the vehicle does not allow the driver to transform the interior elements into working or relaxation mode (e.g., recline the seat backwards), and thus providing physical restraints to avoid undesired biomechanical distractions. When a take-over is requested, the interior elements could automatically transform to the manual driving mode, for instance through re-configuration of the seat and the steering wheel to assist the driver with rapidly establishment of motor readiness.

Sleeping at the wheel may pose a large safety threat as long as drivers ought to take over within certain time budgets

Studies presented in Chapter 3, 4 and 5 belong to the few existing ones that investigated driver take-over performance after having eyes closed for some period of time. The eyes-closed condition generated the few high take-over times among all trials performed within this thesis, by participants appearing to have fallen asleep before the TOR onset, even though closing their eyes was just for 8 minutes. The only post-transition crash also occurred in this condition although the participant claimed his readiness by pressing the button. These results suggest that sleeping at the wheel may have the largest impact on the drivers' take-over performance among all task conditions. Sleeping drivers would completely lose situation awareness, and need considerable amount of time to be awakened and to restore cognitive and sensory-motor functions (Kaduk, Roberts, & Stanton, 2020; Wörle, Metza, Othersenb, Baumann, 2020; see Tassi & Muzet, 2000 for sleep inertia). The biomechanical distractions that may come along, such as sitting with the seatback in the most reclined position, would add to the difficulties to rapidly resume manual control after sleeping. Strict measures must be taken to prevent driver from sleeping during automated driving as long as critical takeovers may occur. For example, upon detection of extreme sleepiness and sleep onset, the system would issue warnings and require the driver to stop the vehicle and take a rest or only allow this in conditions for which the system knows it can drive reliably for a longer period of time.

Drivers should be supported for a period of time after the control transition to manual

Findings from this thesis suggested impact of platoon driving on subsequent manual driving performance. After decoupling from a platoon, drivers may drive with reduced TWH for a couple of minutes. Several previous studies also pointed to carryover effects of driving automation on drivers' attention allocation (e.g., Miller & Boyle, 2019; Vogelpohl, Kühn, Hummel, Gehlert, &Vollrath, 2018), such as reduced focus on road centre, longer eyes-off-road glances, and inadequate mirror checks. These findings suggest that drivers should be supported through this vulnerable period of performance recovery. Possible means can be HMIs that remind the driver to maintain a safe THW, guide the driver to perform safety checks immediately after resuming control, and direct drivers' attention towards critical areas on the road. However, cautions should be exercised that these HMI interfaces may induce additional distractions, increase driver workload and have their own reliability issues. When decoupling from a platoon, the system could also automatically increase the THW to a safe threshold before asking the driver to take over control. If dedicated lanes were to be implemented, a transition area following the end of the automation zone would allow the driver to recover manual driving performance in a safe environment before entering public roads.

Multiple approaches should be combined to ensure road safety of automated driving

The discussions above suggest that multiple approaches need to be combined to manage variability within and between drivers and ensure driving safety at different levels of automation. Driver state monitoring systems could assess if discrepancies between the driver's current state and the desired state exist. If so, the system can issue advisory notifications or warnings, or adjust driving modes to dissolve the discrepancies. Upon detection of extremely risky states according to clearly defined criteria or rules, such as sleeping onset or not having hands on the wheel where imminent takeovers could occur, the system should stop drivers from using driving automation functions until they resume minimum required states. This thesis also cautions that driver state monitoring and prediction has its limits, and additional measures should be taken to ensure road safety. For example, the system should actively and effectively communicate with the driver the current status of the vehicle and uncertainties in the driving environment, and thus prompt the driver to adjust their state accordingly. Besides implementation of digital HMI, the layout of cabin elements can be designed to regulate drivers' non-driving posture and engagement in non-driving activities according to the current task demand, and assist drivers with a fast resumption of motoric readiness if needed. In the end, fallback options should be available whenever possible in case the driver cannot respond adequately in takeover.

8.2 Recommendations for future research

In the end of this thesis, some boundaries of the studies performed within the scope of this thesis are discussed, based on which recommendations for future research are proposed.

First, all empirical studies in this thesis, and the large majority of the take-over studies included in the meta-analysis, were conducted in driving simulators. Virtual and simplified driving environments in a simulator generally raise issues of ecological validity, such as reduced risk perception and workload. Also worth mentioning is that participants may tend to respond in favour of the hypothesis of the study and behave well under observation (see Nichols & Maner, 2008 for "the good-subject effect"). To what extend can the findings be generalized to real-life scenarios needs further investigation, even though various studies have showed at least relative validity (Kaptein, Theeuwes, & Van der Horst, 1996; Riener, 2010; Risto & Martens, 2014; Walker, Hauslbauer, Preciado, Martens, & Verwey, 2019).

In addition, only a small variety of experiment conditions could be examined in the empirical studies, and the periods of automated driving were short (4 – 15 min). Limited insight was gained on drivers' behaviour in naturalistic settings, and the effects of prolonged driving automation on driver states and take-over performance. In the platooning studies, only four task conditions were implemented under well controlled environment, each lasting for less than 10 minutes. The traffic volume was low throughout the platoon driving simulation, while driver's takeover performance, subsequence car following behaviour, and preferred THW could be substantially different in high traffic volume conditions. In the car driving simulator study investigating effects of monitoring requests, a pedestrian crossing the road was the only scenario presented, and fixed time budgets for the monitoring request (12 s) and the take-over request (5 s) were used, which might have led to participants' familiarization and expectation with the critical situations and reduced take-over response times. In each drive, only five MRs and two TORs were issued over the span of 15 min, and it still remains a question how drivers' compliance with MR change in long term use.

Research in this thesis made a unique contribution to the literature by exploring driver behaviour during and right after decoupling from a highly automated platoon and the effects of monitoring requests that adapt to the uncertainty of the driving environment. Future research could expand the analysis to more realistic situations and test a larger variety of scenarios. Particularly, efforts can be made to investigate driver behaviours in prolonged, naturalistic use of automation, to explore impact of sleeping at wheel on driver take-over performance, and to understand how drivers interact and comply with adaptive automation systems. These will provide valuable input for the development of an effective human-in-the-loop adaptive automation system.

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Summary

Driving automation holds great promise for safer and more efficient road transportation, and is becoming a reality thanks to the rapid advancement of technology. However, before full driving automation arrives, the driver would have to take over control of the vehicle when the system fails or reaches its operational limits, which poses new road safety risks at different stages of development. When the system is less capable and reliable, the driver has to closely monitor the system and take over imminent control when necessary. This challenges humans' inherent weak point of staying vigilant over a prolonged period of time. When the technology becomes more mature, the driver would be allowed to engage in a wide range of non-driving tasks, but occasional human interventions still cannot be avoided. How to ensure drivers in various mental and physical states to take over control safely become a major challenge at this stage. A large number of studies have tackled human factors issues related to control transitions, and suggested that no single take-over time budget applies to all drivers in all situations. While an adaptive approach is called for to support individual drivers in taking over control, a better understanding of driver take-over process and the variability between and within drivers is still needed to achieve this goal.

This PhD thesis addresses the challenges stated above and contributes to designing safe and comfortable control transitions to manual. A particular focus was on control transitions in truck platooning scenarios, which have received only limited attention despite of the significance of platooning technology. The first objective is to explore factors influencing the take-over response time and its variability, and to gain a deeper insight in the actual take-over process. The second objective is to systematically study professional drivers' take-over performance in truck platooning scenarios, in order to deliver input for the development of platooning systems and the corresponding infrastructures. The third objective is to design and evaluate potential approaches that prime drivers for a safe and smooth take-over, and to discuss the feasibility of an adaptive and personalized control transition approach.

The first part the thesis (**Chapter 2**) presents an exhaustive meta-review of 129 studies that reported mean take-over response times, aiming to provide the state of the art on driver take-over research, and to explore determinants of take-over times on an aggregated level. Three complementary approaches were employed: (1) a within-study analysis, in which differences in mean take-over time were assessed for pairs of experimental conditions, (2) a between-study analysis, in which correlations between experimental conditions and mean take-over times were assessed, and (3) a linear mixed-effects model combining between study and within-study effects. The three methods showed that a shorter mean take-over time is associated with a higher urgency of the situation, not using a handheld device, not performing a visual non-driving task, having experienced another take-over scenario before in the experiment, and receiving an auditory or vibrotactile take-over request as compared to a visual-only or no take-over request. It is also found the mean and standard deviation of the take-over time were highly correlated, indicating that the mean is predictive of variability. These findings point to directions for new research, in particular concerning the distinction between drivers' ability and motivation to take over, and the roles of urgency, biomechanical distraction, and prior experience.

The meta-review showed that hardly any take-over studies were performed in platooning context. To fill in the research gap, **the second part** of the thesis (**Chapter 3-6**) presents four empirical driving simulator studies investigating driver take-over performance when leaving highly automated truck and car platoons.

- **Chapter 3** and **Chapter 4** describe two truck platooning studies investigating professional truck drivers' take-over performance in non-critical scenarios. In both studies, three task conditions were implemented during platoon driving, namely monitoring without non-driving task, interacting with a tablet PC, and relaxing with eyes closed. The difference between the two studies lies in whether the tablet PC was holding in the hands or mounted on the centre console. Results showed substantially longer take-over times with high variability when the driver was using a hand-held tablet or relaxing with eyes closed, compared to monitoring the road or using a mounted tablet PC. By measuring perception-response times instead of merely total take-over times, hand movement response time was found to be the dominant component of the total take-over time, being influenced by the motoric manoeuvres to resume physical readiness before taking over control (e.g., putting away the hand-held tablet, putting on/off reading glasses, adjusting seating position). Analyses of post-transition manual driving performance showed that truck drivers could stabilize the truck within 10-20 s after the transition in all task conditions, and suggested potential carry-over effects involving small gaps during platooning. In response to a brake event immediately after the control transition, all drivers successfully avoided colliding with the decelerating front truck, except for one driver in the eyes-closed condition. These findings suggest the importance to focus on both cognitive and motoric preparation phases before resuming manual control, and pointed to the potential risk of resuming manual driving after sleeping or relaxing with eyes closed.

- As platooning technology can be applied to both heavy and light vehicles, **Chapter 5** explores behavioural similarities and differences between car drivers and professional truck drivers. This study compares professional truck drivers' take-over performance when leaving a highly automated platoon (as reported in Chapter 4) to that of car drivers measured in the same driving simulator (with a different vehicle model and mock-up) using the identical experimental design. Compared to car drivers, truck drivers took over control more slowly when using a hand-held tablet due to a slower hand movement response; drove more steadily with a larger time gap after the transition; and braked more quickly and less aggressively in response to the decelerating lead vehicle. These findings in general suggest a more cautious manual driving style in professional truck drivers after decoupling from the platoon. In addition, both driver groups showed reduced time headways after the transition, suggesting again carry-over effects of platoon driving involving small gaps.

- For drivers in the truck platoon, monitoring surrounding traffic environment and foreseeing upcoming hazardous situations is very difficult due to very short inter-vehicular distances and consequently a heavily blocked front view. **Chapter 6** explores whether providing drivers in a truck platoon with additional visual information of the traffic environment can influence their monitoring pattern and increase awareness of upcoming critical situations. Twenty-two professional truck drivers were divided into two groups, either following a see-through lead truck (i.e., with projection of forward scene attached to the rear of the lead truck), or a normal lead truck until the automation system failed unexpectedly in a critical situation. Results showed that when provided with front view projection, the drivers spent 10% more time monitoring the road, and responded less severely to a critical situation, suggesting positive effects of the "see-through" technology. Nevertheless, such technology did not affect their take-over times in a critical situation.

In on-road settings, it is not feasible to always allow sufficient time budgets for drivers in various states to take over safely, neither is it realistic to require prolonged effective driver monitoring. **In the third part** of the thesis (**Chapter 7**), a design solution was proposed and evaluated that may bridge the gap between automated with a driver out of the loop and completely manual driving. An HMI concept was designed that provides a monitoring request (MR) when approaching a location where driver take-over is likely to be requested. The MR asked the driver to pause the non-driving task, monitor the traffic environment, and be prepared for a potential take-over. If a critical event was detected, the system provided a take-over request (TOR) as well. The aim is to stimulate a dynamic allocation of monitoring tasks to human and automation that adapts to the system capability and the situation complexity, and to better prepare drivers to take over safely and efficiently. In the simulator-based experiment with 41 participants, the effects of the MR+TOR system were assessed by comparing to a conventional system that only issued TORs. Results showed that the MR+TOR system improved participants' take-over performance in terms of shorter take-over response time and longer minimum time collision, and yielded more positive subjective ratings regarding workload, trust, and acceptance. Because only a small portion out of all MRs require an actual driver take-over, an additional analysis was conducted to investigate how drivers' compliance with MRs was associated with previously experienced scenarios. Although drivers showed good overall compliance by looking up to the road in response to MRs in all cases, hand and foot preparatory behaviour appeared to deteriorate after experiencing an MR without a critical event, and increased after a take-over event. These findings suggest that the cry-wolf effects may be a concern in the use of MR, and measures should be applied to stimulate proper trust calibration.

My PhD thesis provided a comprehensive research on factors influencing driver take-over response times, made an initial contribution to the understanding of driver behaviour during and right after decoupling from a highly automated platoon, and proposed an innovative HMI design to better prepare drivers for potential critical take-overs. The findings suggested that dynamically changing driver states and driving situation predominantly determine the driver's capability to take over control safely at a specific moment. While a driving automation system that can adapt to individual drivers' states has potential to increase driving safety during transitions, one should also foresee the limit in providing precise estimations of a specific drivers' take-over readiness. Multiple approaches need to be combined to manage variability within and between drivers and ensure driving safety at different levels of automation, such as actively communicating with the driver the current status of the vehicle and uncertainties in the driving environment, designing cabin layout to regulate drivers' non-driving posture and engagement in non-driving activities according to the current task demand, and providing fallback options whenever possible in case the driver cannot respond adequately in takeover.

Samenvatting in het Nederlands

Volledig automatisch rijden kan in potentie voor veiligere en efficiëntere mobiliteit zorgen. Dankzij technologische vooruitgang wordt volledig automatisch rijden realiteit in de nabije toekomst. Echter, voordat de volledige rij-automatisering er aankomt zal er een fase zijn waarbij de bestuurder de controle over het voertuig incidenteel overneemt, bijvoorbeeld wanneer het systeem uitvalt of de limieten van het systeem worden bereikt. Deze tussenfase van de ontwikkeling van automatisering zullen leiden tot nieuwe veiligheidsrisico's. Wanneer het systeem nog niet volledig automatisch en betrouwbaar is, zal de bestuurder het systeem en het verkeer moeten blijven monitoren om direct de controle over te nemen wanneer dat noodzakelijk is. Hiermee wordt een inherent zwak punt van de mens aangesproken namelijk om gedurende een langere periode waakzaam te blijven (vigilantie) en de status van het systeem en het verkeer te volgen. Wanneer de technologie volwassener wordt, zou de bestuurder een breed scala aan niet-rijdende taken oftewel secundaire taken mogen uitvoeren. Echter incidentele menselijke tussenkomst kan dan nog noodzakelijk zijn. Het wordt een uitdaging om ervoor te zorgen dat in deze fase van de technologieontwikkeling bestuurders in verschillende mentale en fysieke toestanden de controle van het voertuig veilig kunnen overnemen. Een aantal studies hebben de factoren die verband houden met de wisseling van de controle tussen mens en voertuigautomatisering onderzocht, en komen daarbij tot de conclusie dat er geen standaard overnametijd kan worden gebruikt voor een veilige overname van de controle van het voortuig door de bestuurder. Hoewel een adaptieve aanpak wordt gesuggereerd om individuele bestuurders te ondersteunen bij het overnemen van de controle, is een beter begrip van het overnameproces van bestuurders en de variabiliteit tussen en binnen bestuurders nodig om dit doel te bereiken.

Dit proefschrift gaat in op de hierboven genoemde uitdagingen en draagt bij aan het ontwerpen van veilige en comfortabele overgang van automatische naar handmatige voertuigbediening. Bijzondere aandacht ging uit naar controle-overgangen in scenario's voor het platoonen van vrachtwagens, die ondanks het onderschreven belang van platooning slechts beperkte aandacht hebben gekregen. Het eerste doel is om te onderzoeken welke factoren de overnametijd en de variabiliteit daarvan beïnvloeden, om inzicht te krijgen in het daadwerkelijke overnameproces. Het tweede doel is om systematisch de overnameprestaties van professionele chauffeurs te onderzoeken in scenario's voor vrachtwagenplatooning, om zo input te leveren voor de ontwikkeling van platooningsystemen en de bijbehorende infrastructuren. De derde doelstelling is het ontwerpen en evalueren van mogelijke benaderingen om de bestuurder te attenderen en voor te bereiden op een veilige en soepele overname. En tenslotte wordt de haalbaarheid van een adaptieve en gepersonaliseerde overgang van de controle behandeld.

Het eerste deel van het proefschrift (**Hoofdstuk 2**) presenteert een uitputtende meta-review van 129 onderzoeken die gemiddelde overnameresponstijden rapporteerden, met als doel de stand van de techniek te verschaffen op het gebied van onderzoek naar het overnemen van de controle door bestuurders en om factoren die de overname beïnvloeden te onderzoeken op een geaggregeerd niveau. Er werden drie complementaire benaderingen gebruikt: (1) een analyse, waarbij verschillen in gemiddelde overnametijd werden beoordeeld van experimentele condities binnen dezelfde studie (2) een analyse tussen studies, waarin correlaties tussen experimentele condities en gemiddelde overname tijden werden beoordeeld, en (3) een linear mixed-effects model die deze twee analyses combineert.

De drie analyses toonden aan dat een kortere gemiddelde overnametijd gepaard gaat met: een hogere urgentie van de situatie, dat er geen technologie gebruikt wordt, dat er geen secundaire visuele taak wordt uitgevoerd, dat men eerder in het experiment een ander overnamescenario heeft meegemaakt, en het ontvangen van een multimodaal (auditief en/of tactiel) overnameverzoek, dit in vergelijking met een visueel of geen overnameverzoek. Ook blijkt dat het gemiddelde en de standaarddeviatie van de overnametijd sterk gecorreleerd waren, wat aangeeft dat het gemiddelde voorspellend is voor variabiliteit. Deze bevindingen geven aanwijzingen voor nieuw onderzoek, in het bijzonder met betrekking tot het onderscheid tussen het vermogen en de motivatie van bestuurders om de controle over te nemen, en de rol van urgentie, biomechanische afleiding en eerdere ervaring van de bestuurder.

Uit de meta-review bleek dat er nauwelijks overnamestudies werden uitgevoerd in de context van platooning. Om de lacune in het onderzoek te dichten, bestaat **het tweede deel** van het proefschrift (**Hoofdstuk 3-6**) uit vier empirische rijsimulatorstudies die de overnameprestaties van bestuurders onderzoeken bij het verlaten van geautomatiseerde auto- en vrachtwagenplatoons.

- **Hoofdstuk 3** en **Hoofdstuk 4** beschrijven twee platooning studies die de overnameprestaties van professionele vrachtwagenchauffeurs onderzochten in niet-kritieke scenario’s. In beide onderzoeken waren er drie condities tijdens het besturen van een platoon, namelijk monitoren zonder extra secundaire taak, interactie met een tablet, en ontspannen met gesloten ogen zitten. Het verschil tussen de twee studies was de tablet conditie. Waarbij in de ene studie de tablet in de handen werd gehouden, werd in de andere studie de tablet op de middensconsole gemonteerd. De resultaten lieten aanzienlijk langere overnametijden zien met grotere variabiliteit wanneer de bestuurder een draagbare tablet gebruikte of ontspande met gesloten ogen, vergeleken met het monitoren van de weg of het gebruik van een tablet in de console. Door perceptie-reactietijden te meten in plaats van louter de totale overnametijden, bleek dat bewegingsreactietijd de dominante component was bij de totale overnametijd. Deze bewegingsreactietijd werden beïnvloed door de motorische handelingen die nodige waren ter voorbereiding om de controle van het voertuig over te nemen (bijv. de draagbare tablet opbergen, een leesbril opzetten/ afzetten, de zitpositie aanpassen). Analyses van het rijgedrag na de overgang naar handmatig rijden toonden aan dat vrachtwagenchauffeurs de truck binnen 10-20 seconden na de overgang in alle condities konden stabiliseren, en suggereerden een mogelijk overdrachtseffect van het rijden in een platoon waarbij iets minder ruimte werd gelaten tot de voorganger na de handmatige overname. Als reactie op een plotselinge remactie onmiddellijk na de overgang van de controle, konden alle chauffeurs met succes een botsing met de vertragende voorste truck vermijden, behalve één chauffeur in de conditie waarbij de ogen gesloten waren. Deze bevindingen suggereren het belang om te focussen op zowel cognitieve als motorische voorbereidingsfasen voordat handmatige controle wordt hervat, en wezen op het potentiële risico van het hervatten van handmatig autorijden na het slapen of ontspannen met gesloten ogen.

- Platooning technologie kan zowel bij vrachtwagens als bij auto's worden toegepast, **Hoofdstuk 5** behandelt overeenkomsten en verschillen in gedrag van automobilisten en professionele vrachtwagenchauffeurs. Dit onderzoek vergelijkt de overnameprestaties van professionele vrachtwagenchauffeurs bij het verlaten van een sterk geautomatiseerd platoon (zoals gerapporteerd in Hoofdstuk 4) met die van automobilisten gemeten in dezelfde rijsimulator (met een ander voertuigmodel en mock-up) met behulp van hetzelfde experimentele ontwerp. In vergelijking met automobilisten waren vrachtwagenchauffeurs langzamer bij de overname van de controle wanneer zij een tablet vasthielden vanwege een tragere handbeweging; zij reden gelijkmatiger met een grotere afstand tot de voorligger na de overgang; en remde sneller en minder hard in reactie op de afremmende voorligger, het voorste voertuig van de platoon. Deze bevindingen suggereren over het algemeen een behoedzame handmatige rijstijl bij professionele vrachtwagenchauffeurs na ontkoppeling van het platoon in vergelijking tot de automobilisten. Daarnaast vertoonden beide bestuurdersgroepen een kortere volgtijd tot de voorligger na de overgang naar handmatig rijden, wat duidt op wederom overdrachtseffecten van het rijden in een volledig geautomatiseerd platoon met korte volgafstanden.

- Voor vrachtwagenchauffeurs die rijden in een platoon is het waarnemen van het omringend verkeer en het anticiperen van een mogelijke gevaarlijke situaties lastig. Dit vanwege de zeer korte volgafstanden tussen de voertuigen, waardoor het zicht naar voren sterk belemmerd wordt. In **Hoofdstuk 6** wordt het effect van extra visuele informatie vastgesteld: het monitoren van de verkeerssituatie en het anticiperen op mogelijke kritieke verkeerssituaties. Tweeëntwintig vrachtwagenchauffeurs werden verdeeld in twee groepen, de eerste groep reed achter een doorzichtige voorste vrachtwagen, d.w.z. met een projectie van de verkeerssituatie aan de achterkant van de voorste vrachtwagen. De tweede groep reed achter een normale voorste vrachtwagen. Beide groepen reden in een automatisch rijdend platoon, totdat het automatiseringssysteem onverwachts uitviel. De resultaten toonden aan dat wanneer de chauffeurs zicht hadden op de verkeerssituatie door projectie op de achterkant van de vrachtwagen, de chauffeurs 10% meer tijd besteedden aan het monitoren van de weg en minder abrupt reageerden op een kritieke situatie. Dit wijst op positieve effecten van de projectietechnologie, toch had deze projectietechnologie geen invloed op hun overnametijden in de kritieke situatie.

Op de weg is het niet haalbaar om bestuurders in verschillende staat van alertheid altijd voldoende tijd te geven om de controle over het voertuig veilig over te nemen. En het is evenmin realistisch om van de bestuurder te eisen langdurig alert te blijven en het systeem te monitoren. **In het derde deel** van het proefschrift (**Hoofdstuk 7**) wordt een ontwerpoplossing voorgesteld en geëvalueerd die de kloof kan overbruggen tussen automatisch rijden en volledig handmatig rijden. Er is een HMI-concept ontworpen dat zorgt voor een monitoringverzoek (Monitoring

Request; MR) bij het naderen van een locatie waar de bestuurder waarschijnlijk wordt gevraagd om de controle over te nemen. De MR vroeg de bestuurder om de secundaire taak te onderbreken, de verkeerssituatie te inspecteren en voorbereid te zijn op een mogelijke overname. Als er een kritieke verkeerssituatie werd gedetecteerd, stelde het systeem ook een overnameverzoek voor (Take-Over Request; TOR). Het doel is om een dynamische toewijzing van controletaken aan mens en automatisering te stimuleren die zich aanpast aan de systeemcapaciteit en de complexiteit van de situatie, en om bestuurders beter voor te bereiden om het rijden veilig en efficiënt handmatig over te nemen. In dit simulator experiment met 41 bestuurders, waarbij de effecten van het MR+TOR-systeem werden beoordeeld door vergelijking met een conventioneel systeem dat alleen TOR gebruikte. De resultaten toonden aan dat het MR + TOR-systeem de overnameprestaties van de bestuurders verbeterde in termen van een kortere reactietijd bij de overname en een langere minimal time-to-collission, en meer positieve subjectieve beoordelingen opleverde met betrekking tot mentale werklast, vertrouwen en acceptatie. Omdat slechts een klein deel van alle MR's een daadwerkelijke overname van de chauffeur vereistte, is een aanvullende analyse uitgevoerd om te onderzoeken hoe de naleving van MR's door bestuurders beinvloed werd door eerder ervaren scenario's. Hoewel bestuurders over het algemeen een goede naleving lieten zien door in alle gevallen naar de weg te kijken als reactie op MR's, leek het voorbereidende gedrag van handen en voeten te verslechteren na het ervaren van een MR zonder een kritieke gebeurtenis, en het voorbereidend gedrag nam toe na een voorgaand secnario met een overname. Deze bevindingen suggereren dat de foutpositieven een punt van zorg kunnen zijn bij het gebruik van MR, en dat er rekening gehouden moet worden met het stimuleren van een adequate mate van vertrouwen in het systeem.

Mijn proefschrift bevat een uitgebreid onderzoek naar de factoren die van invloed zijn op overname reactietijden tijden van bestuurders. Het levert een bijdrage aan het begrip van het rijgedrag tijdens en direct na het ontkoppelen van een automatisch rijdend platoon en stelt een innovatief HMI-ontwerp voor om bestuurders beter voor te bereiden op mogelijke kritieke overnames. De bevindingen suggereerden dat dynamisch veranderende mentale en fysieke toestanden van bestuurders en verkeerssituaties voornamelijk bepalend zijn voor het vermogen van de bestuurder om op een bepaald moment de controle veilig over te nemen. Hoewel een adaptief systeem voor automatisch rijden zich kan aanpassen aan de toestand van individuele bestuurders, en daarmee de rijveiligheid tijdens overgangen kan verhogen, is dit vooralsnog ook gelimiteerd door het vermogen nauwkeurige accurate schattingen te geven van overname responsetijden van specifieke bestuurders. Meerdere benaderingen moeten worden gecombineerd om variantie binnen en tussen bestuurders mee te nemen tijdens verschillende niveaus van rijautomatisering om de verkeersveiligheid te kunnen garanderen. Zoals actief communiceren met de bestuurder over de huidige status van het voertuig en verkeerssituaties, het ontwerpen van de cabine om de niet-rijdende houding van chauffeurs en betrokkenheid bij secundaire activiteiten in overeenstemming te brengen met de huidige taakvereiste en het bieden van back-up mogelijkheden waar mogelijk, voor het geval de chauffeur niet adequaat kan reageren bij de overname van de controle van het voertuig.

About the author

Bo Zhang was born on August, 28th 1988 in Harbin, Heilongjiang, China. Bo graduated from the Technical University of Munich in September 2015 with the M. Sc. degree in Human Factors Engineering. In her master thesis, she investigated commercial airline pilots' manual skill degradation induced by extensive use of Autopilot systems and a lack of on-the-job practice. Before starting her study in Germany, Bo obtained her B. Sc. degree in Industrial Design at Harbin Institute of Technology, China, in 2011. In January 2016, Bo joined the Department Centre for Transport Studies at the University Twente as a Marie Curie Fellow in the Project HFauto – Human Factors of Automated Driving. She investigated car and truck drivers' behaviour and performance when taking over control from automated driving in various conditions, aiming to provide implications for achieving a safe and smooth control transition back to manual.

In her spare time, Bo is an enthusiast and practitioner of contemporary visual art. Since 2019, she has been undertaking part-time Bachelor Programme in Fine Arts at the Gerrit Rietveld Academy in Amsterdam. Fascinated by how art evokes universal emotions in people from all around the world, Bo wonders what makes us human and forms the basis for universal communication across cultures, and hopes to contribute to safe and seamless human-system interactions that are accessible and beneficial to all people regardless of their social, cultural, or personal characteristics.

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