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Lu, Zhenji

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Human Factors of Transitions in Automated Driving

Zhenji Lu

Delft University of Technology, The Netherlands

Human Factors of Transitions in Automated Driving

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Zhenji LU

Joint Master of Science in Complex Systems Science

University of Warwick, United Kingdom and University of Gothenburg, Sweden

Master of Science in Control Science and Engineer

Harbin Institute of Technology, China

born in JiXi, China

This dissertation has been approved by the promotors.

Composition of the doctoral committee:

Rector Magnificus	chairperson
Dr. ir. J.C.F. de Winter	Delft University of Technology, promotor
Dr. ir. R. Happee	Delft University of Technology, promotor

Independent members:

Prof. dr. ir. D.A. Abbink	Delft University of Technology
Prof. dr. M.P. Hagenzieker	Delft University of Technology
Prof. dr. N. Merat	University of Leeds, United Kingdom
Prof. dr. H. de Ridder	Delft University of Technology
Dr.ir. M. Wang	Delft University of Technology

CONTENTS

SUMMARY

In the last decades, advanced driver-assistance systems have contributed to improved road safety. With the recent advance of technology, automotive automation is taking more and more tasks away from the driver. Although automation removes human imprecision and variability, it also introduces out-of-the-loop problems such as complacency, skill degradation, mental underload, mental overload, and loss of situation awareness. Additionally, the rising levels of automation have contributed to an increasingly complex interaction between the automation and the driver, where driver and automation may have to change roles while driving. The objective of this PhD thesis is to understand what types of 'transitions' occur between the automation and the driver, how drivers process visual information to rebuild situation awareness and make decisions during these transitions, and how to make the transitions from automation to human safer and more acceptable for the driver.

The topic of transitions of tasks between the automation and the driver has become an important topic in the research community. Chapter 2 proposes a theoretical framework to support and align human factors research on transitions in automated driving. "Driving states" are defined based on the allocation of three primary driving tasks: longitudinal control, lateral control, and monitoring. Monitoring transitions and control transitions are the two types of transitions in automated driving. Based on essential principles of task allocation, three questions/actions were used to define various types of control transitions: 'Is the transition required?', 'Who initiates the transition?', and 'Who is in control after the transition?'. The corresponding six control transitions between automation and the driver are (1) Optional Driver-Initiated Driver-in-Control, (2) Mandatory Driver-Initiated Driver-in-Control, (3) Optional Driver-Initiated Automation-in-Control, (4) Mandatory Driver-Initiated Automation-in-Control, (5) Automation-Initiated Driver-in-Control, and (6) Automation-Initiated Automation-in-Control. Using the proposed framework, previous experimental studies on transitions in automated driving and use cases were listed, interpreted, and summarised.

"Automation-Initiated Driver-in-Control" transitions of control, where drivers need to take back control after a take-over request provided by the automation, are critical to road safety. The driver first needs to rebuild situation awareness in such scenarios. Chapter 3 investigates how long it takes for drivers to build up situation awareness of a traffic scenario. Thirty-four participants viewed different durations (1, 3, 7, 9, 12, or 20 s) of video clips of traffic scenarios on a monitor, in which an eye tracker was integrated. After viewing the video, participants reproduced the state of the vehicles by placing the cars in a graphical user interface (i.e. GUI) with indications of relative speed to the ego car that is the participants'

own simulated car. Results showed that participants' global situation awareness of the number of cars in the video increased with increasing time budget and reached a stationary level between 7 and 12 s video lengths. The eye-tracking results showed that glance frequencies to the mirrors decreased with observation time, which could mean that participants directed their attention to individual cars after estimating the spatial pattern of all cars.

Building upon this concept, Chapter 4 adds the challenge of dealing with safety-critical situations (hazards). Thirty-two participants watched simulated video clips with lengths between 1 and 20 s, while their eyes were recorded using eye-tracking equipment. The perspectives of the videos were similar to those in Chapter 3. The simulated video clips in Chapter 4 contained either no hazard or an impending crash in the form of a car slowing down to standing still in the ego lane. After each video, participants were asked to (1) decide on a manoeuvre after the end of the scene (no need to take over, evade left, evade right or brake only), (2) rate the danger of the situation, (3) rebuild the final situation from a top-down perspective, and (4) rate the difficulty of the rebuilding task. From the results of self-reported danger and pupil diameter, it was inferred that the hazard situations were experienced as clearly more dangerous than the non-hazard situations. However, the hazards did not affect participants' rebuilding task performance or self-reported difficulty scores. An exception occurred for the shortest time budget (1 s) videos, where the situation awareness of the participants was impaired by the front hazard; this hazard inhibited participants from visually scanning the rear-view mirror. In this study, participants showed only a 75% decision accuracy in hazardous scenarios with a 9 s time budget, which indicates taking over control in emergency conditions will be difficult for human drivers. How to assist drivers during transitions of control (besides giving more time budget) is still a significant challenge for academic researchers and the industry.

Much effort in academia and the automobile industry has been made to develop systems that guarantee safety after automation disengagements. The automated driving system could be designed so that it performs certain backup safety functions to avoid human errors in time-critical conditions. An alternative way of interaction is proposed in Chapter 5. By allocating primary driving task dynamically via monitoring requests (MRs) and take over requests (TORs), drivers may prepare for the transitions better. MRs are possible in real-automated cars due to the development of navigation technology, such as HD maps. Forty-one drivers participated in a simulator-based study in which MRs and TORs were presented. An MR was triggered 12 s before a zebra crossing as a precaution, and in the MR+TOR condition, a TOR

would be triggered (5 s before crashing into the pedestrians) if pedestrians actually crossed the road. In the TOR-only condition, the TOR was not preceded by an MR. The results showed that the MRs directed the drivers' visual attention to the road, and that drivers subsequently performed better at the transitions-of-control task. Also, the drivers reported a lower workload, higher acceptance, and higher trust experienced in MR+TOR condition comparing to the TOR-only condition.

The framework of driving states and transitions, which describes how primary tasks are allocated between the driver and the automation, provides a new holistic view of the roles for the driver and automation. The subsequent studies showed the effects of time budget and traffic situation on participants' decision-making and situation awareness. Finally, an innovative way of interaction was designed for planned control and monitoring transitions. The results showed that making the provision of monitoring requests preceding take-over requests provides a more acceptable and safer experience for the driver of the automated vehicle as compared to take-over requests only.

CHAPTER 1

INTRODUCTION

Cars are equipped with more and more automation systems. Such automated driving systems can increase traffic efficiency, energy efficiency, and road safety (Alkim, Bootsma, & Hoogendoorn, 2007; Kuehn, Hummel, & Bende, 2009; Fagnant & Kockelman, 2015; Kühn & Hannawald, 2014; Kyriakidis, Happee, & De Winter, 2015; Meyer & Deix, 2014; Watzenig & Horn, 2017). Most car manufacturers have released systems with Level 1 and 2 (defined by SAE International, 2016) automated driving technology, such as adaptive cruise control (ACC) or/and lane centring control (LCC) systems. Several companies, such as Tesla and Audi, have released automated lane changing functions with embedded HD maps. These products release drivers from part of the control tasks in certain operational domains while the drivers are still required to constantly stay in the cognitive loop. Naturally, more advanced automated driving systems will expand their operational domain, and allow drivers to be out of the loop and perform non-driving tasks. This next step is called Level 3 automation (SAE, 2016) or high automation (BASt; Gasser, & Westhoff, 2012). With these systems, the driver has to resume the driving task after a warning signal (also called a take-over request) issued by automation.

Before entering the automated vehicle era, new safety challenges need to be addressed. These safety challenges concern the human factors during transitions of primary task allocations between the automation and the driver. As Flemisch et al. (2016) argued, the 'uncanny valley' will emerge in the intermediate stages of technology developments where human drivers are expected to react to emerging scenarios. The problem is that humans are not good at supervisory tasks and cannot be expected to remain vigilant for long periods (Casner, Hutchins, & Norman, 2016; Norman, 2015, Hancock, 2015; Mackworth, 1950). Similar problems have been extensively discussed in the human factors research community. Skill degradation, mental underload/overload, loss of situation awareness, and complacency problems caused by out-of-the-loop conditions may occur with the introduction of automation (Bainbridge, 1983; Bibby, Margulies, Rijnsdorp, & Withers, 1975; Endsley & Kiris, 1995; Hancock et al., 2013; Kaber & Endsley, 1997; Parasuraman & Riley, 1997; Vlakveld, 2015; De Winter, Happee, Martens, & Stanton, 2014).

'Taking over control' is a primary task left for the human operator who supervises an automated system (Bainbridge, 1983). Similarly, in automated driving, drivers need to take-over control after automation failure or after the automation reaches its operational limits. Drivers put in these situations are likely to underperform in complicated traffic conditions with limited time budget (e.g., De Waard, Van der Hulst, Hoedemaeker, & Brookhuis, 1999;

Flemisch, Kelsch, Löper, Schieben, & Schindler, 2008; Jamson, Merat, Carsten, & Lai, 2013; Schermers, Malone, & Van Arem, 2004; Zeeb, Buchner, & Schrauf, 2015). Therefore, the transition process requires attention from researchers in academia and the automated driving industry.

1.1   Scope of the dissertation

In many empirical studies, including the aforementioned ones, drivers were put in particular simulated traffic situations with or without non-driving tasks to perform. In these studies, drivers had to take over control to avoid a collision (or a traffic violation) after an automation disengagement or take-over request. However, the lack of a theoretical framework to define these transitions makes it challenging to derive general conclusions from these experiments. The cognitive processing elements during the transitions would also need more investigations (apart from knowledge on what control inputs the automated system needs from the human driver). Furthermore, there is a need for an HMI design that improves drivers' experiences and safety during transitions.

1.1.1   Not Just 'Takeover'

Transitions in automated driving have previously been defined either as function (de)activations (Gold, Damböck, Lorenz, & Bengler, 2013a; Miller, Sun, & Ju, 2014; Nilsson, Falcone, & Vinter, 2015; Pauwelussen & Feenstra, 2010; Toffetti et al., 2009) or as changes from one level of automation to another (Merat, Jamson, Lai, Daly, & Carsten, 2014; Varotto, Hoogendoorn, Van Arem, & Hoogendoorn, 2015; Willemsen, Stuiver, Hogema, Kroon, & Sukumar, 2014). To define transitions, in the period between two different states (Flemisch et al., 2012), the definition of 'states' in automated driving needs to be reconsidered first

The different levels of control in complex car driving tasks (e.g., Michon, 1985) can be simplified to three following three primary driving tasks: (1) lateral control, (2) longitudinal control, and (3) monitoring, as also presented in BASt and SAE. The differentiation of longitudinal and lateral manoeuvres aligns with well-accepted taxonomies of driving tasks (e.g., McKnight & Adams, 1970). The task allocations between the driver and the automation can be used to define the driving states in automated driving. Such a definition of driving states differs from the existing BASt, SAE, and NHTSA levels of automation, because the levels of automation describe what the driver and automation are doing rather than what they

should be doing. Such a new approach to defining driving states could give a more precise description of transitions from a human factors perspective.

1.1.2 'Time' Matters

The focus of many studies has been on the available time for taking over control (sometimes referred to as 'time budget') and drivers' take-over time, which is the time driver take to steer or brake (SAE, 2016; Zeeb, Buchner, & Schrauf., 2016, Clark & Feng, 2015; Gold et al., 2013a; Mok, Sirkin, Sibi, Miller, & Ju, 2015; Kerschbaum, Lorenz, & Bengler, 2015; Van den Beukel & Van der Voort , 2013; Samuel, Borowsky, Zilberstein, & Fisher, 2016; Merat et al., 2014) . Zhang, De Winter, Varotto, Happee, and Martens (2019) reviewed 129 experimental studies on take-over time budget to find out the determinants of take-over time. That study showed that, among other factors, the urgency of the simulated traffic situation and take-over request modality influenced how quickly drivers took over. However, more insights need to be offered into the cognitive processes during the take-over tasks; this includes the rebuilding of situation awareness as well as decision-making.

Situation awareness, defined as 'knowing what is going on so you can figure out what to do' (Adam, 1993), is an important prerequisite for a high-quality take-over decision. Even though some studies indicated that take-over times could be as short as one second (e.g., Cohen-Lazry & Katzman, 2018; Politis, Brewster, & Pollick, 2017), such a short amount of time is insufficient for achieving situation awareness. Zeeb, Buchner, and Schrauf (2016) showed that drivers' motor reaction (e.g., grabbing the steering wheel) could be rapid, even when situation awareness was still impaired. Drivers will probably need much more than one second time to rebuild situation awareness (Samuel et al, 2016). Therefore, the time required for rebuilding SA in all conditions, including hazard and non-hazard conditions, is worth investigating.

1.1.3 Monitor, Please

In Chapter 2, transitions in automated driving were classified into control transitions and monitoring transitions. Most of the human factors literature has focused on control transitions (e.g., studies of take-over time), while monitoring transitions and control transitions can occur independently. For instance, the driver could monitor the road to acquire situation awareness without physically taking over control. A concept of monitoring requests (MRs) was previously implemented by Gold, Lorenz, Damböck, and Bengler (2013b) in a driving

simulator. The goal of this design was to initiate a monitoring transition to prepare drivers for a possible TOR. The authors suggested that MRs could be beneficial for safety by comparing results to their previous study (Gold et al., 2013a).

In the literature, several concepts exist that are similar to MRs, such as likelihood alarm systems (e.g., Balaud, 2015; Wiczorek, Balaud & Manzey, 2015) and presentations of automation uncertainty/capability (Beller, Heesen, and Vollrath, 2013, Dziennus et al., 2016; Helldin, Falkman, Riveiro, & Davidsson, 2013; Yang et al., 2017). However, these continuous information systems demand constant attention, and are easily neglected during non-driving related tasks. Louw et al. (2017a, 2017b) applied an uncertainty alert upon the detection of a lead vehicle, with the aim to examine the relationship between drivers' eye movement patterns and crash outcomes. A number of other studies used the concept of "soft-TOR" or "two-step TOR" to direct the driver's attention to the traffic before the driver had to take over control (Lapoehn et al., 2016; Naujoks, Purucker, Neukum, Wolter, & Steiger, 2015; Van den Beukel, Van der Voort, & Eger, 2016; Willemsen, Stuiver, & Hogema, 2015). Based on the above studies, it seems that the provision of MRs is promising for redirecting attention in automated driving. However, a direct comparison was still needed for evaluation of the effects of the MR concept with a system that provides only a TOR.

1.2 Dissertation outline

This dissertation consists of one theoretical study (Chapter 2) and three empirical studies (Chapters 3–5). The results of the studies are summarized, and recommended further investigations and applications are discussed in Chapter 6.

Chapter 2 builds the theoretical background of driving states (based on task allocations) and transitions, which include control transitions and monitoring transitions between driving states. A classification tree was introduced to categorize different types of control transitions based on the role of initiations and responsibility of the transitions. Experimental studies are interpreted using our transitions framework for verification.

Chapter 3 investigates the situation awareness rebuilding process as a function of time budget in non-hazardous traffic in a PC-based experiment. The SAGAT-like (Situation Awareness Global Assessment Technique) method of Gugerty (1997) was refined here to examine the effect of available time (1, 3, 7, 9, 12 or 20 s) on situation awareness scores prior to a transition of control. In this study, several dependent measures were used for a comprehensive perspective; these measures include (1) self-reported task difficulty and time

sufficiency, (2) the absolute error between the number of placed cars and the actual number of cars, (3) the error between the positions and indicated speeds of the placed cars relative to the actual positions/speeds of the cars, and (4) the geometric difference between the positions of the placed and actual cars.

Chapter 4 further examines participants' performance in hazard situations and their ability of decision-making for different time budgets, using a similar method as in Chapter 3. In addition to verification of the results from Chapter 3, the effect of the presence of a hazard on situation awareness was investigated. Furthermore, the participants were required to make decisions (no need to take over, evade left, evade right, or brake) before the rebuilding task, to investigate the relationship between decision making and situation awareness.

Chapter 5 implements a monitoring request when a take-over is likely to occur in addition to take over request. This within-subject driving simulator study looked into drivers' monitoring state, driving performance, as well as subjective experience for an MR+TOR system compared to a baseline system that provided TORs only. It was examined whether drivers responded to the MR by looking at the road when requested, and performance in control transitions tasks if requested.

In the end, Chapter 6 summarises the main findings, future applications and remaining gaps from these studies.

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CHAPTER 2

HUMAN FACTORS OF TRANSITIONS IN AUTOMATED DRIVING: A GENERAL FRAMEWORK AND LITERATURE SURVEY

Abstract

The topic of transitions in automated driving is becoming important now that cars are automated to ever greater extents. This paper proposes a theoretical framework to support and align human factors research on transitions in automated driving. Driving states are defined based on the allocation of primary driving tasks (i.e., lateral control, longitudinal control, and monitoring) between the driver and the automation. A transition in automated driving is defined as the process during which the human-automation system changes from one driving state to another, with transitions of monitoring activity and transitions of control being among the possibilities. Based on 'Is the transition required?', 'Who initiates the transition?', and 'Who is in control after the transition?', we define six types of control transitions between the driver and automation: (1) Optional Driver-Initiated Driver-in-Control, (2) Mandatory Driver-Initiated Driver-in-Control, (3) Optional Driver-Initiated Automation-in-Control, (4) Mandatory Driver-Initiated Automation-in-Control, (5) Automation-Initiated Driver-in-Control, and (6) Automation-Initiated Automation-in-Control. Use cases per transition type are introduced. Finally, we interpret previous experimental studies on transitions using our framework and identify areas for future research. We conclude that our framework of driving states and transitions is an important complement to the levels of automation proposed by transportation agencies, because it describes what the driver and automation are doing, rather than should be doing, at a moment of time.

2.1   Introduction

Car driving is becoming automated to an ever greater extent. Presently, most car manufacturers have released cars that are equipped with adaptive cruise control (ACC) and/or lane keeping assistance (LKA) systems, which are technologies that assist in the longitudinal and lateral driving tasks, respectively. In field operational tests, these driver assistance systems have been found to raise traffic efficiency and to reduce energy consumption (e.g., Alkim, Bootsma, & Hoogendoorn, 2007). Moreover, such systems may reduce the number of traffic accidents (Kuehn, Hummel, & Bende, 2009), most of which are currently attributed to human error (Brookhuis, De Waard, & Janssen, 2001; Dingus et al., 2006; Storie, 1977; Treat et al., 1979).

The existing driver assistance systems function as supportive automation and keep the driver in the loop by requiring the driver to monitor the environment and control part of the driving task. More advanced technologies that allow the driver to be out-of-the-loop for extended periods are now starting to be introduced. Three authorities, namely the German Federal Highway Research Institute (BASt; Gasser & Westhoff, 2012), the Society of Automotive Engineers (SAE, 2014), and the United States National Highway Traffic Safety Administration (NHTSA, 2013) have each formulated definitions that classify automated driving systems from driver assistance to full automation. In fully automated driving, the automation takes care of all monitoring and control activities, and a driver is not strictly needed anymore other than to set a destination. However, several problems, such as limitations of technology, divergent public acceptance, liability issues, and human-machine ethics, are yet to be solved before fully automated driving can become publicly available at a wide scale (e.g., Kyriakidis, Happee, & De Winter, 2015).

Previous human factors research indicates that automation resolves the imprecision and variability of human task performance, but also yields new types of safety concerns. It has been found that a high level of automation can cause out-of-the-loop problems such as complacency, skill degradation, mental underload (when the automation functions reliably), mental overload (when the operator suddenly needs to solve an automation-induced problem), and loss of situation awareness (Bainbridge, 1983; Bibby, Margulies, Rijnsdorp, & Withers, 1975; Endsley & Kiris, 1995; Hancock et al., 2013; Kaber & Endsley, 1997; Parasuraman & Riley, 1997; Vlakveld, 2015), which are issues that have also been implicated in the domain of automated driving (De Winter, Happee, Martens, & Stanton, 2014; Seppelt & Victor, 2016;

Young & Stanton, 2002). Recently, a meta-analysis of 18 experiments on human-automation interaction found statistical support for the so-called lumberjack hypothesis, which postulates that as the degree of automation increases, the side effects of automation (e.g., performance impairment if the automation fails) increase as well (Onnasch, Wickens, Li, & Manzey, 2014). In the domain of automated driving, it has been argued that not the highest levels of automation, but intermediate levels in which the human is expected to monitor the automated driving system, may be particularly hazardous because humans are unable to remain vigilant for prolonged periods of time (Casner, Hutchins, & Norman, 2016; Norman, 2015). These studies make clear that due to the changes in the driver's role in automated vehicles compared to manually driven vehicles, human factors need to be carefully considered by researchers, designers, and policy makers (see also Kyriakidis et al., 2016; Merat & Lee, 2012).

Bainbridge (1983) argued that 'taking over control' is a primary task left for the human operator who supervises an automated system. Indeed, one cannot ignore the fact that automated driving systems will occasionally fail (Goodall, 2014), which implies that a driver has to resume control to avoid crashing. Moreover, automated driving systems of the near future will probably not be able to cover all traffic conditions, which implies that the driver has to take over control to avoid a collision or traffic violation. Empirical studies have confirmed that accidents and near-accidents are likely to occur in situations where drivers suddenly have to resume manual control from an automated driving system (e.g., De Waard, Van der Hulst, Hoedemaeker, & Brookhuis, 1999; Flemisch, Kelsch, Löper, Schieben, & Schindler, 2008; Jamson, Merat, Carsten, & Lai, 2013; Schermers, Malone, & Van Arem, 2004; Zeeb, Buchner, & Schrauf, 2015). The aforementioned out-of-the-loop problems exacerbate the inability of the driver taking back control from automation. Thus, it is important to investigate control transitions in automated driving, especially when considering that human factors studies have repeatedly demonstrated that humans are not good at supervisory tasks (Hancock, 2015; Mackworth, 1950).

One issue that occurs when interpreting the experimental literature on control transitions is that the results are much determined by the specific automation functions, traffic conditions, and task instructions (see De Winter et al., 2014 for a review). To be able to derive more general conclusions on driver behaviour across different automated driving systems and traffic situations, this paper proposes a framework that defines and classifies transitions focusing on changes of driving states. This framework is intended to build a dialogue among researchers who share common interests in understanding how drivers behave during

transitions in automated driving. Our concept of driving states differs from the existing BASt, SAE, and NHTSA levels of automation because it formally outlines possible allocations of primary driving tasks and is descriptive rather than normative. That is, our framework describes what the automation and driver are doing at a given moment of time (descriptive approach) rather than what they should be doing according to design criteria/standards of conduct (normative approach).

This paper is organised as follows. Section 2 defines transitions between driving states. We explain that the driving states represent how the primary driving tasks of longitudinal control, lateral control, and monitoring are distributed between the automation and the driver, and that transitions are defined as a change from one driving state to another. Section 3 introduces a classification tree that categorizes different types of control transitions. In Section 4, we review experimental studies that are concerned with transitions in automated driving, and interpret the findings using our transitions framework. Finally, Sections 5 and 6 present research gaps and draw conclusions arising from this review and applications of the new framework.

2.2   Definition of transitions in automated driving

Most studies on transitions in automated driving have defined a 'transition' as either an activation or a deactivation of a function (Gold, Damböck, Lorenz, & Bengler, 2013; Miller, Sun, & Ju, 2014; Nilsson, Falcone, & Vinter, 2015; Pauwelussen & Feenstra, 2010; Toffetti et al., 2009), or a change from one level of automation to another (Merat, Jamson, Lai, Daly, & Carsten, 2014; Varotto, Hoogendoorn, Van Arem, & Hoogendoorn, 2015; Willemsen, Stuiver, Hogema, Kroon, & Sukumar, 2014). Similarly, Merriam-Webster defines a 'transition' as 'a change from one state or condition to another', whereas Flemisch et al. (2012) stated that a transition is the period between two different states. In summary, it can be argued that determining the 'states' based on driving tasks is a prerequisite for defining a 'transition' in automated driving.
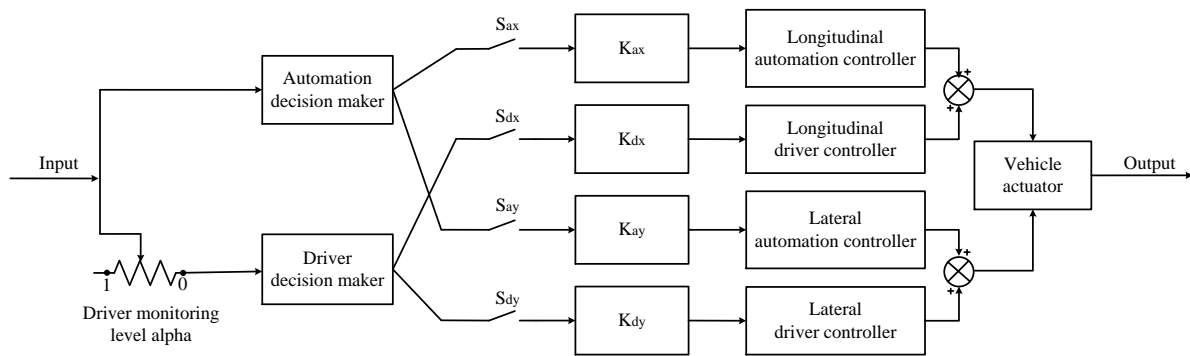
2.2.1   Driving tasks

Car driving is a highly complex task that can be modelled at different levels of control with different levels of temporal granularity (e.g., Michon, 1985). We parsimoniously consider the following three primary driving tasks: (1) lateral control, (2) longitudinal control, and (3) monitoring, which are also present in the BASt, SAE, and NHTSA definitions of

levels of automated driving. Our distinction between longitudinal and lateral control is also congruent with many models of vehicle control (e.g., Rajamani, Tan, Law, & Zhang, 2000) and driver performance (e.g., Nash, Cole, & Bigler, 2016), and with well-known taxonomies of driving tasks that distinguish between longitudinal (starting, accelerating, stopping) and lateral (steering, lane changing, curve driving) manoeuvres (e.g., McKnight & Adams, 1970).

Although the BAST, SAE, and NHTSA definitions differ from each other, the criteria these organisations adopt to classify the levels of automation are similar (SAE, 2014). The essential criteria are how the three primary driving tasks (i.e., lateral control, longitudinal control, and monitoring) are distributed between the driver and the automation. For example, the difference between Assisted Driving (AD) and Partially Automated Driving (PAD) as defined by BASt is that in PAD the automation takes over both lateral and longitudinal control, while only one of these is automated in AD. This distinction between AD and PAD is equivalent to the distinction between Driver Assistance and Partial Automation in the SAE definition, and between 'Level 1 Function-Specific Automation' and 'Level 2 Combined Function Automation' in the NHTSA definition. Furthermore, the BASt definition says that the difference between PAD, HAD, and Fully Automated Driving (FAD) is the required monitoring frequency which decreases from 'permanently' in PAD, to 'need not permanently' in HAD, and 'need not' in FAD. This decrease in monitoring frequency with increasing level of automation is also present in the SAE and NHTSA definitions. Two other criteria that have been used to define the levels of automation are (1) system capability (i.e., the type of scenario [e.g., low speed traffic jam, merging] that the automated driving system is able to drive in) and (2) fall-back agent (i.e., whether the automation or the driver is expected to take back control of monitoring and control tasks after an automation failure), see SAE (2014). These latter two criteria are important from a legal and design perspective, but are not adopted in the present study because they mix expected behaviour (i.e., what the driver and the automation should be doing in specific environmental conditions) with actual behaviour.

When describing the distribution of the primary driving tasks between driver and automation at a given moment of time, a diagram can be drawn as shown in Figure 1. This figure illustrates the lateral/longitudinal control and monitoring of a vehicle by the automation and the driver. Here, Input is the state of the vehicle (e.g., velocity and acceleration) and environmental information (e.g., traffic signs and surrounding road users). Output is the state of the vehicle in the environment, one system step after the input. The Driver decision maker (a human agent) and the Automation decision maker (a computer agent) acquire and analyse

the Input and determine the steering and acceleration target signals. Note that both the driver and automation decision makers are higher-level information processors rather than low-level trajectory-following controllers. (S_{ax}, S_{dx}) and (S_{ay}, S_{dy}) allocate control for the longitudinal and lateral directions between driver and automation, respectively, and (K_{ax}, K_{dx}) and (K_{ay}, K_{dy}) represent proportional weights of driver and automation. The target signals (e.g., steering angles and acceleration) are fed to the longitudinal and lateral driver or automation controllers, the switches, and the proportional parameters. The longitudinal and lateral controllers constitute transfer functions that generate steering and throttle/brake control signals. The vehicle actuators implement these signals to move the vehicle.

Figure 1. Diagram describing the distribution of driving tasks (lateral control, longitudinal control, monitoring) between the driver and the automation. dx = driver longitudinal; dy = driver lateral; ax = automation longitudinal; ay = automation lateral; S = switch, K = proportional gain. In this diagram, the decision makers determine a target signal which is executed by lower-level longitudinal and lateral controllers.

Note that Figure 1 does not include a switching unit that sets the switches, and therefore does not establish *who* initiates a control transition and what the transition criteria are. Moreover, our framework is concerned with defining actual transitions (rather than attempted transitions or the consequences of transitions gone wrong), and so does not depict failure modes such as a sensor or actuator failure, exceedances of functional constraints, or mode errors (cf. Sarter & Woods, 1995). Furthermore, it is worth emphasizing that Figure 1 describes the current state of the driver-automation system; it does not describe the temporal sequence of a transition from the start of a transition (e.g., driver input or take-over request) to the end of a transition (i.e., when the agents have control of the task they were requesting or requested to have).

In Figure 1, it is assumed that the automation permanently monitors the environment because repetitive monitoring is where machines excel with respect to humans (cf. Fitts, 1951; De Winter & Hancock, 2015). The driver, on the other hand, is not a permanent monitor of

the environment. The *alpha* level represents how much input information is fed to the Driver decision maker. Specifically, *alpha* at a particular moment should be regarded as a one-dimensional variable that describes the driver's monitoring activity for gaining situation awareness (cf. Endsley, 1995). *Alpha* is dependent on the driver's mental status, such as his workload and arousal level. We use *alpha* = 0 to represent a situation where the driver does not monitor the road and so receives no information and achieves no awareness of the current driving situation, such as when the driver is asleep behind the wheel. *Alpha* = 1 means that the driver actively monitors the environment so that he/she is fully aware of 'what is going on'.

The *recommended* level of *alpha* in automated driving is a function of the primary driving task allocation. In a review article, Flemisch et al. (2012) described the relationships between driver ability, responsibility, and control. Their framework shows that (1) responsibility motivates control, (2) control causes responsibility, and (3) control is enabled by ability. From their framework, we infer that if the driver is controlling, the driver has to monitor as well (i.e., *alpha* = 1) for the driving condition to be safe, or put differently, it is irresponsible to control a car without monitoring.

2.2.2 *Definition of static driving states*

Before defining transitions in automated driving, we need to define the driving states of automated driving. A driving state represents the primary driving tasks (lateral control, longitudinal control, monitoring) which the driver and automation are executing at a given moment.

We define a static driving state as a situation where control is performed either by the driver or by the automation. This means that K_{ax}, K_{dx}, K_{ay} and K_{dy} are equal to 1, and only one switch is turned on in each pair of switches (S_{ax}, S_{dx}) and (S_{ay}, S_{dy}). Six static driving states are possible according to the state of the switches and the monitoring level *alpha*:

- State 1: S_{dx} and S_{dy} are both switched on, S_{ax} and S_{ay} are both switched off, and *alpha* is 1. This state is manual driving.
- State 2.1: S_{ax} and S_{dy} are both switched on, S_{dx} and S_{ay} are both switched off, and *alpha* equals 1 (because the driver is still engaged in lateral control tasks). This state represents driving assistance with longitudinal automation such as ACC.
- State 2.2: S_{dx} and S_{ay} are both switched on, S_{ax} and S_{dy} are both switched off, and *alpha* equals 1 (for the same reason as in State 2.1). This state represents driving

assistance with lateral automation only (cf. Carsten, Lai, Barnard, Jamson, & Merat, 2012; Young & Stanton, 2007).

- State 3: S_{ax} and S_{ay} are both switched on, S_{dx} and S_{dy} are both switched off, and *alpha* is still 1. This state maps to driving with lateral and longitudinal automation. The driver is monitoring permanently to be able to take over control anytime needed.

- State 4: S_{ax} and S_{ay} are both switched on, S_{dx} and S_{dy} are switched off, but unlike State 3 the driver is not monitoring permanently (i.e., *alpha* is between 0 and 1).

- State 5: The conditions of the switches are the same as in States 3 and 4, but the driver is not monitoring at all (i.e., *alpha* equals 0).

It is worth emphasizing that the above states represent what the driver and automation are actually doing, not necessarily what they should be doing or are capable of doing. For example, a driver-automation system with a driver who is monitoring permanently is classified as State 3, whereas for another driver who is using the same automation technology but does not monitor permanently, this human-automation system is classified as driving State 4.

The driving states listed above do not include 'irresponsible' driving states. Such driving states could in principle be added without altering the topology of Figure 1. An example is when S_{dx} and S_{dy} are both switched on, S_{ax} and S_{ay} are both switched off, and *alpha* is smaller than 1, which corresponds to distracted manual driving (cf. Dingus et al., 2016). Moreover, we cannot ignore the fact that situations may exist in which both the automation and the driver do not control one or both of the primary control tasks. Such a situation occurs when S_{ax} and S_{dx} are both switched off, and/or S_{ay} and S_{dy} are both switched off. We did not classify such situations as a driving state because neither agent actually performs the driving task. If such a situation is safety-critical, the automation may attempt a pre-programmed action to bring the car into minimal risk condition (see also SAE, 2014).

2.2.3 Dynamic driving state

It is also possible that the human and automation are jointly executing the same control task whereby the degree of control is dynamically adjusted to the momentary situation. One type of such human-machine interaction is shared control (Abbink, Mulder, & Boer, 2012; De Winter & Dodou, 2011; Johns et al., 2016; see also Sheridan, 2002; Sheridan & Verplank, 1978), a concept which has been extended towards a framework of 'cooperative control' (Flemisch, Bengler, Bubb, Winner, & Bruder, 2014). A distinction between dynamic and

static driving states has also been made by Inagaki (2003) who stated: "Sharing and trading are distinguished to clarify the types of human-automation collaboration" (p. 147).

Accordingly, we define a dynamic driving state as a situation where the driver and automation are executing at least one driving control task together. This means that both switches are turned on in one or both pairs of the switches (S_{ax}, S_{dx}) or (S_{ay}, S_{dy}). The weight variables (K_{ax}, K_{dx}), (K_{ay}, K_{dy}) can be set according to the level of control of driver and automation. Note that some authors have proposed a 'coupling valve', rather than binary switches, as a conceptualization of the extent to which driver, automation, and vehicle are cooperatively in control of the driving task (Baltzer, Altendorf, Meier, & Flemisch, 2014). Also note that in Figure 1, we showed the weight variables as proportional gains for reasons of simplicity and interpretability; the actual control system design can obviously be more complex than this. As with any mathematical-psychological model (MacCallum, 2003), the model shown in Figure 1 does not fully account for all complexities of real driving, but aims to parsimoniously represent the key phenomena of interest.

In shared control, the driver always executes a control task, which may alleviate out-of-the-loop problems such as loss of situation awareness (e.g., Abbink et al., 2012). Several assistance systems currently make use of shared control, whereby an assistive force is provided on the accelerator in order to support car following or eco-friendly driving, or on the steering wheel in order to guide the driver back into its lane or to prevent colliding with a road user in the blind spot (see Petermeijer, Abbink, Mulder, & De Winter, 2015, for a review). The BASt, SAE, and NHTSA levels of automated driving do not account for the concept of shared control, because these definitions characterize the driving tasks in terms of 'trading' of control (cf. Inagaki, 2003) through terminology such as 'taking over control' and by allocating monitoring, task-execution, and fallback-performance functions to the human driver versus the automated driving system. It is currently being investigated what the role of shared control may be in future automated driving systems (Johns et al., 2016; Mok, Johns et al., 2015). The results thus far indicate that shared control may be promising as an optional driving mode to keep the driver informed and involved, especially when the automation drives imperfectly (Abbink et al., 2012; Flemisch et al., 2014; Mok et al., 2015).

2.2.4   *Definition of transitions*

Based on the above concept of driving states, a transition can be defined as a process during which the driver-automation system changes from one driving state to another driving

state. For example, a transition from State 4 to 1 means that the driver resumes both longitudinal and lateral control, and that the monitoring level is set to 1.

Flemisch et al. (2008) included all possible control transitions in a spectrum of automation. We refine this spectrum by making a distinction between monitoring transitions and control transitions. Transitions among States 3, 4, and 5 concern changes in the driver's monitoring status. A transition of control refers to a transition that involves a reallocation of the longitudinal or lateral control task between the driver and the automation. For some of the control transitions, the corresponding changes of monitoring level (e.g., monitoring level increases from 0 to 1 during the transition from State 5 to State 1) are not shown, because the recommended level of monitoring is determined by whether or not the human is in control, as explained above. Figure 2 illustrates the overall concept.

| State 1 | State 2.1 | State 2.2 | State 3 | State 4 | State 5 |
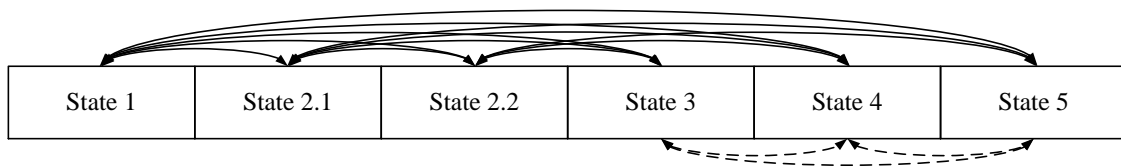
Figure 2. Monitoring transitions and control transitions between different driving states. Solid lines represent control transitions, whereas dashed lines represent monitoring transitions.

2.3 *Classification of transitions of control*

Transitions of control have a direct influence on the speed and path of the vehicle, and therefore have a direct relationship with road safety. A classification of control transitions facilitates understanding of the task demands on drivers during a transition. We classify transitions of control based on a retrospective account of a successfully completed transition, to avoid ambiguities regarding the causality of attempted or unsuccessful transitions.

In a prior literature review, Martens et al. (2008) classified the possible control transitions in automated driving. In their research, three questions were used to classify control transitions between the driver and automation: (1) Who has 'it'?, (2) Who should get 'it'?, and (3) Who initiates transition?, yielding four types of transitions: (1) driver-initiated, from the driver to the automation ($D_i \rightarrow A$), automation-initiated, from the driver to the automation ($D \rightarrow A_i$), (3) driver-initiated, from the automation to the driver ($D_i \leftarrow A$), and (4) automation-initiated, from the automation to the driver ($D \leftarrow A_i$). Hoeger et al. (2011) provided an extended notation by including transitions between different levels of automation. For example, a driver-initiated transition from highly automated (HA) driving to driver-assisted

driving was designated as follows: $DA_i \leftarrow HA$. Furthermore, Hoeger et al.(2011) introduced a notation for describing failed/refused transitions, which may occur when the activation of a particular automation mode is impossible.

We chose to deviate from the above transition classifications for several reasons. First, we argue that if a transition occurs then control will always transfer from one agent to the other (i.e., from the automation to the driver, or from the driver to the automation), and so there is no need of including both agents in the definition of a transition. Second, because we are concerned with actual transitions rather than with intended transitions, we did not consider failed transitions in our classification. Moreover, what is an intended and failed transition will be difficult to define in formal terms (for insightful reflections on the definition of 'error', see Sharit, 2006; Reason, 2013). Third, the underlying reasons for transitions are not included in the above classifications, in particular whether the transition is required or optional.

2.3.1 Classification tree of transitions of control

Our first dimension in the classification of control transitions is 'Who initiates the transition?', defined as who actually initiates the transition of the *control* task (i.e., not including changes in monitoring activity). Prior research indicates that *who* initiates a transition (i.e., human or automation) is an important question in the design of adaptive automation and function allocation in general. Thus, a distinction can be made between human-initiated transitions and automation-initiated transitions (Hancock, 2007; Inagaki & Sheridan, 2012; Scerbo, 1996).

The second dimension is 'Who is in control after transition?' This dimension includes two possibilities (automation and driver). It is important to define who is in control after a transition, because whoever is in control is responsible for the safe execution of the driving task.

Because the initiation of a transition is a discrete event while the control abilities of driver and automation are continuously changing, we use 'initiation of transition' and 'control after transition' as the first and second branch of our classification tree (Fig. 3). The corresponding two transition categories are 'driver-initiated transitions' and 'automation-initiated transitions'. Each of the two primary categories is divided into two subcategories: 'driver in control' and 'automation in control'. Based on these two criteria, we identify four types of transitions: 'Driver Initiates transition, and Driver in Control after (DIDC)', 'Driver Initiates transition, and Automation in Control after (DIAC)', 'Automation Initiates transition, and Driver in

Control after (AIDC)', and 'Automation Initiates transition, and Automation in Control after (AIAC)'.

The third level in the classification refers to the underlying reason for the transition. At this third level, transitions are clustered into two categories: optional transitions and mandatory transitions. An optional transition occurs when there is no requirement or decision rule that stipulates that a transition should happen (i.e., the transition is voluntary), and the driver who prefers a transition implements the transition. Conversely, a mandatory transition occurs when the agent that is in control before the transition follows a rule or is required to relinquish control (i.e., the transition has to happen). Thus, optional transitions can be described as will-based, whereas mandatory transitions can be understood as ability-based or rule-based. In our framework, optional transitions are always initiated by the driver. At the present state of technology, automation does not have the option ('free will') to choose the control tasks based on its preference, because the decision rules that are used by automation are built in its software. We recognize that developments in artificial intelligence may eventually lead to synthetic consciousness and create the possibility of optional automated-initiated transitions, but this is beyond our current scope. Thus, driver-initiated transitions can be optional or mandatory, whereas automation-initiated transitions can only be mandatory. Similarly, Varotto et al. (2015) classified transitions while driving with ACC as mandatory and discretionary transitions.

Achieving better and safer performance is one of the reasons for using automation. How and when to use automation are difficult questions that have been debated for over a century or more (e.g., Hollnagel, 2012). The answers to these questions are not only a matter of technology, but also involve social and ethical dimensions (e.g., Hancock, 2014; Hancock, 2015; Sheridan, 1970; Sheridan, 1980). Well known in science fiction are the 'three laws of robotics' by Asimov (Asimov, 1942). Some alternative principles have also been developed based on real world situations (Murphy & Woods, 2009). Within the scope of this paper, we will not discuss social or ethical aspects in much detail. Nevertheless, we propose the following practical function allocation criteria inspired by Asimov's laws: 1) in case of an imminent collision, the automation should take control in order to protect humans by avoiding collision or by reducing the severity of impact, and 2) the automated car (with or without the driver inside) should try to avoid damage to itself, but not in such a way that it harms a human or conflicts with the driver's orders. Of course, these simple rules do not solve all ethical intricacies such as trolley problems of various kinds (cf. Bonnefon, Shariff, & Rahwan, 2015;

Goodall, 2014), but they may be a useful starting point for defining mandatory versus optional transitions.

2.3.2   *Use case analysis for each category of the control transitions*

Below, we adopt a use case analysis to analyse the interactions between the driver and the automated driving system for various types of transitions as defined in Figure 3.
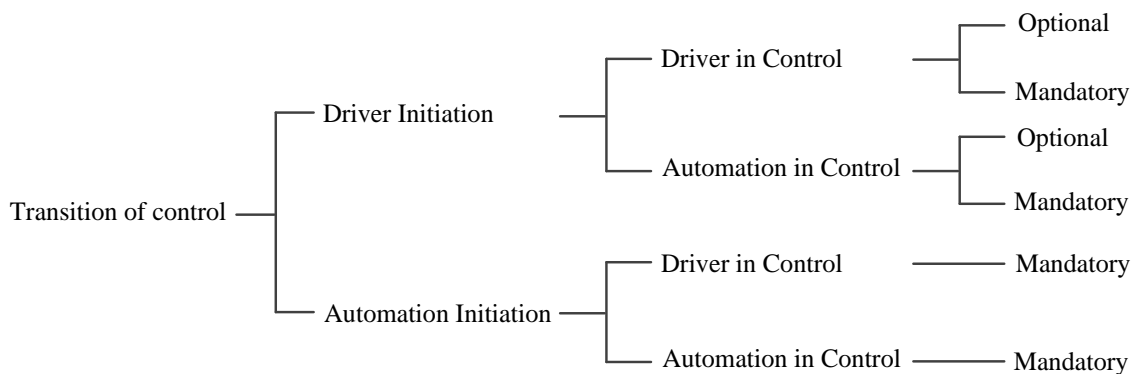
Figure 3. Classification tree of transitions of control.

2.3.2.1 Optional Driver-Initiated transitions

During an optional DIDC or optional DIAC transition, both the automation and the driver will usually have the ability to control the vehicle. An example is a driver who turns on (i.e., optional DIAC transition) or turns off (i.e., optional DIDC transition) the ACC on the highway in a non-critical situation. Because both agents are able to drive, this use case is less critical for safety than mandatory transitions where one of the agents is unable to control the vehicle. In this use case, the automation may suggest to the driver that it is possible to make a transition. Note that if the automation offers a suggestion about a possible transition, this does not make it an automation-initiated transition, because it is still the driver who makes the decision and initiates the transition of control. The low criticality and ordinary character of DIAC and DIDC transitions may explain why much of the research on optional driver-initiated transitions has investigated when, where, and why drivers initiate a transition of control (Klunder, Li, & Minderhoud, 2009; Pauwelussen & Feenstra, 2010; Varotto et al., 2015; Viti, Hoogendoorn, Alkim, & Bootsma, 2008). Of course, not all optional DIAC and DIDC transitions are safe; it is possible that the driver initiates a transition at an inappropriate moment or by accident, whereby he hands over control to the automation while the automation is less able than the driver in the current environmental conditions (e.g., when driving in snow), or conversely, where the driver takes control while the automation is more

capable than the driver (e.g., close car following in a high-speed platoon or when *alpha* is low).

2.3.2.2 Mandatory Driver-Initiated transitions

A mandatory DIDC transition can be initiated when the driver diagnoses that the automation is unable to drive, whereas a mandatory DIAC transition is initiated when the driver thinks he himself is unable or not allowed to drive. For instance, a DIDC transition can be initiated when the driver diagnoses an automation failure without warning from the automation. A DIAC transition can happen when the driver has a physical emergency, such as a heart attack, or a 'cognitive emergency', such as information overload. Another example is that in future intelligent traffic consisting of platoons of automated vehicles (e.g., Hsu, Eskafi, Sachs, & Varaiya, 1993; Van Arem, Tampere, & Malone, 2003), entering a platoon may require a DIAC transition to let the host vehicle's automation cooperate with other vehicles and infrastructure automatically. Overall, driver-initiated transitions require clear information on the automation's (in)capability of driving, signalling the need for a proper human-machine interface (Inagaki, 2003).

2.3.2.3 Automation-Initiated transitions

An automation-initiated transition can be triggered by the automation's diagnosis regarding the driving inability of the automation itself, or regarding the inability of the driver who was controlling the vehicle before the transition. An AIDC transition may be caused by an exceedance of the automation's operational limits or by a computer failure that is detected by on-board diagnostics, a scenario also known as a 'take over' (Gold, Damböck et al., 2013). Another possibility is 'adaptive automation', whereby the automation hands over control to the human in an attempt to raise the driver's situation awareness or to reduce other out-of-the-loop problems (Gonçalves & Bengler, 2015; Hoeger et al., 2011; Merat et al., 2014; Rauch, Kaussner, Krüger, Boverie, & Flemisch, 2009; Whitmore & Reed, 2015). In modern traffic jam assistance systems, for example, the automation may disengage when the driver does not have his/her hands on the steering wheel for a period of time (e.g., between 10 and 30 s, depending on the manufacturer). For such a transition, the driving State is 3, 4, or 5 before the transition, and the driving State is 1 after the transition. This is a mandatory AIDC transition, with the hands-off interval being a predefined rule that is programmed into the automation.

An AIAC transition does not imply that the automation should overrule the human. We recommend that the automation should not make decisions and implement actions without human consent, except in the cases where, through inaction, the human will get hurt. For example, when a driver fails to drive safely during a heart attack, the automation should take over control if it can reliably determine this from a physiological monitoring system. Likewise, if a manual driver fails to react to other vehicles, the automation may temporarily take over control and initiate autonomous emergency braking (AEB) or an evasive manoeuvre. Moreover, similar to mandatory DIAC transitions, mandatory AIAC transitions occur when the driver is required to hand over control according to the rules and regulations of the automated traffic system.

2.3.2.4 Safety criticality of transitions

Similar to how active safety and passive safety are defined, we can classify DIDC and AIAC (which are self-activated transitions) as active transitions, and AIDC and DIAC (which are triggered interventions) as passive transitions. In active transitions (AIAC and DIDC), the agent who initiates the transition is the *same* as the agent who ends up with control. In these two transition types, whoever initiates the transition is usually prepared to take over control afterwards. On the other hand, in passive transitions DIAC and AIDC, the initiating agent and the resulting driving agent are *different* and whoever is in control after the transition may have been forced to take over control from the other agent. In DIAC and AIDC transitions, the agent who is in control before the transition needs to ascertain that the other agent has the ability to drive, and get the other agent prepared for the transition. A lack of preparation may lead to unsafe situations.

In a mandatory DIAC transition, the driver is in control before the transition, and automation control could be unstable after the automation may have been forced to take over control of the car, depending on the situation and environmental conditions. As for AIDC transitions, if drivers do not respond timely and properly, the transition could lead to an accident. The fact that AIDC transitions are essential to the safety of automated driving may explain why these transitions have been extensively studied in driving simulator experiments by human factors researchers. The most common AIDC (i.e., take-over) scenario can be summarized as follows: due to an automation limitation (e.g., the automation detects an accident in front of the host vehicle and cannot cope with this situation), participants are warned to take over control by braking and/or steering within a time margin (e.g., Gold,

Damböck et al., 2013; Lorenz, Kerschbaum, & Schumann, 2014; Radlmayr, Gold, Lorenz, Farid, & Bengler, 2014; Naujoks, Purucker, Neukum, Wolter, & Steiger, 2015; Petermeijer, De Winter, & Bengler, 2016; Telpaz, Rhindress, Zelman, & Tsimhoni, 2015; Willemsen et al., 2014; Zeeb et al., 2015). AIDC transitions have drawn the attention of not only human factors scientists, but also of automotive engineers who are solving the controllability problems that AIDC transitions may cause. For example, Nilsson et al. (2015) proposed a concept whereby AIDC transitions are classified as safe or unsafe by calculating whether the current and predicted vehicle states are within the estimated driver capabilities.

Setting up experimental driving scenarios for a certain transition use case is a challenge, because everything is possible regarding future technologies. The proposed classification tree (Fig. 3) could provide guidance for designing scenarios with a theoretical basis.

2.4   A brief survey of human factors research on transitions of control

In this section, we review previous experimental studies using the above framework of driving states and transitions categories. The goal of this literature review is to interpret the representative empirical literature in light of our framework, and accordingly derive conclusions and recommendations for further research.

Broadly speaking, experimental human factors research on transitions can be clustered into two groups. The first group of research involves transitions between driving States 2/3 and driving State 1, or vice versa. In driving States 2 and 3, the driver constantly monitors the automation status and the outside environment, so the driver is situationally aware. Several human factors studies regarding these three driving states have focused on driver behavioural adaptation and manual driving behaviour after having used the automated driving system (Bianchi, Piccinini et al., 2013; Hoedemaeker & Brookhuis, 1998; Young & Stanton, 2007). Researchers have also examined at which moments drivers activate and deactivate their automation (ACC) system, and have modelled the impact of these transitions on traffic flow (e.g., Klunder et al., 2009; Pauwelussen & Feenstra, 2010; Varotto et al., 2015; Viti et al., 2008).

Our focus is on the second group of research: transitions where the driving state changes from State 4 or 5 to a lower state. A meta-analysis by De Winter et al. (2014) showed that drivers' overall workload while driving in SAE level 3 (driving States 3 and 4) automation is substantially lower than while driving with ACC (driving State 2.1). This low-workload situation is sometimes followed by a high-workload safety-critical AIDC transition (De

Winter et al., 2014). In driving States 4 or 5, the driver is not in control and does not constantly monitor the outside environment (*alpha* < 1). If a control transition involves driving States 4 or 5, this means that the monitoring status will also change during the transition (Fig. 2). The following section discusses control transition studies that involve driving States 4 and 5, and AIDC transitions in particular.

We reviewed experimental research based on the following inclusion criteria: (1) The control transition should involve driving State 4 or 5, (2) The study should focus on driver behaviour during a transition (i.e., studies on long-term adaptation to automated systems were not included), (3) The paper should be in English. We observed that most research on driver behaviour during control transitions clustered into two periods: the late 1990s and the 2010s.

2.4.1 *Control transition studies in the late 1990s*

The first period covers the late 1990s during which several human factors experiments focused on the automated highway system (AHS). Control transitions were necessary when changing lanes from the manual driving lane to the automated driving lane, and vice versa. These studies tried to answer where and how to transition control when entering and leaving the automated lane, and measured the effects on traffic flow efficiency and the driver's preferences. For example, Levitan, Golembiewski, and Bloomfield (1998) argued that a control transition from driving State 1 to driving State 5 should happen *before* entering the automated lane. Buck and Yenamcndra (1997) found that automation-initiated transitions are more time efficient than driver-initiated transitions while entering the automated lane in terms of traffic flow. Furthermore, De Vos, Hoekstra, and Hogema (1997) found that one-step transitions from driving State 5 to driving State 1 were more subjectively preferred than gradual transitions. Note that these studies were based on the anticipation of autonomous vehicles and separated lanes in an AHS. Details regarding driver behaviour during transitions, such as eye gaze patterns, workload, and responses to transitions, were not found to be greatly covered in the 1990s. Results of these early studies generally showed that driver acceptance and driving performance were better when the automation carried on more tasks (i.e., towards the higher side of our driving state scale).

2.4.2 *Control transitions studies from around 2010*

The second period started around 2010 with an increasing number of control transition studies. These more recent studies appear to be more practically relevant than much of the

research from the 1990s, because the recent studies are based on already existing driver assistance systems (cf. 1990s research focusing on envisioned but non-existing AHSs; e.g., De Waard et al., 1999). In addition, these recent experiments focused on driver's behaviour and cognitive states, including such factors as reaction times, control actions, attention allocation, and workload. As we discussed in section 3.2.4, AIDC transitions that require the driver to get back into the control loop are crucial for safety. We selected experimental studies on AIDC transitions based on the following criteria.

First, studies had to describe the type of transition and the driving states before and after the transition in sufficient detail. If the experimental protocol required the driver to engage in a non-driving task that required constant visual attention of the driver (such as the Surrogate Reference Task, SuRT), or if the scenario did not offer any visual information prior to the transition (such as simulation screen blackout), with no reported control of the vehicle and monitoring of the road prior to the transition, we defined the driving state before the transition as State 5. If the participants were requested/reported to engage in an intermittent non-driving task (i.e., a task only took part of their visual attention) or no non-driving task was offered while automation longitudinally and laterally controlled the vehicle, we defined the driving state before the transition as State 4. We noticed that the non-driving task requirements prior to the transition were often reported ambiguously. We emphasize herein that a description of the automated driving technology alone cannot represent how the driver uses the technology. Information on how drivers were tasked and how drivers actually behaved is essential in order to be able to interpret the results of experiments. The second inclusion criterion was that a description of the transition scenario had to be reported. The reason for this inclusion criterion is that the driving behaviour is highly related to the environmental conditions (e.g., Antonson, Mårdh, Wiklund, & Blomqvist, 2009; Kaiser, Wölfing, & Fuhrer, 1999). Third, the physical design and functionalities on the human machine interface (HMI) used for transitions had to be provided or illustrated. As Norman (1990) and many others have argued, feedback about automation status is an important determinant of how humans behave when interacting with automation. An appropriate HMI enables the human to recognize the automation's intentions and to perceive the automation's limitations. HMIs have been used extensively with the aim to improve driver performance and reduce human out-of-the-loop problems in automated systems (Inagaki, 2006; Kaber, Wright, & Sheik-Nainar, 2006).

Table 1 provides an overview of the retrieved studies on AIDC transitions. In several of the experiments, the HMI was an independent variable. Toffetti et al. (2009), for example,

observed that adding vocal messages to a visual-auditory warning increased the drivers' general level of awareness and yielded shorter reaction times in some of the driving scenarios. Naujoks, Mai, and Neukum (2014) found that visual-auditory warnings decreased drivers' reaction times compared to a visual-only warning. Moreover, Lorenz et al. (2014) showed that displaying a heads-up safety corridor in addition to a displayed icon for the driver to steer towards after receiving a take-over request had a positive influence on driving performance compared to driving without the heads-up display. Not only visual and auditory (vocal or acoustic) warnings have been used to bring drivers back to driving State 3 or lower; tactile feedback has been applied as well. Telpaz et al. (2015) found that tactile feedback leads to a faster response time compared to control sessions without tactile feedback, and orients the drivers' attention to the relevant stimuli in the environment.

Table 1 shows that in the AIDC transition experiments, the HMI usually offered a visual-auditory warning. Van den Beukel and Van der Voort (2013) used an auditory warning only, and Merat et al. (2014) used a visual indication only. The use of auditory warnings as take-over requests may be suboptimal when considering that a number of driving studies (Adell, Várhelyi, & Hjälmdahl, 2008; Biondi, Rossi, Gastaldi, & Mulatti, 2014) have shown that beeps can have negative effects on driver performance and satisfaction.

In addition to the display aspects of the HMI, the physical input of the HMI is a relevant design parameter as well. As shown in Table 1, almost all experiments used the steering wheel and pedals to deactivate the automation. In some cases, a button or lever could also be used to deactivate the automation. Furthermore, Kerschbaum, Lorenz, and Bengler (2014) suggested that a coupled steering wheel without visible spokes could improve driving performance during transitions, while decoupled steering wheels (i.e., remaining stationary during automated driving) might not cause negative effects on the transition processes.

A number of experiments assessed driver behaviour after making a transition from driving State 5 to State 3 or lower (Gold, Damböck et al, 2013; Radlmayr et al., 2014; Van den Beukel & Van der Voort, 2013). Generally, it has been found that: 1) The shorter the lead time, the worse the take-over quality (expressed in terms of e.g., percentage of accidents, maximum lateral and/or longitudinal acceleration), and 2) The higher the traffic density, the more time drivers need to regain situation awareness and take over manual control.

Table 1. Retrieved experimental studies on AIDC transitions.

Paper	Traffic scenario	Driving state Before transition	Driving state After transition	Informing interface Visual	Vocal	Acoustic	Tactile	Deactivation interface Button/Lever	Steering wheel	Pedals
Toffetti et al., 2009	The drivers needed to take control from automation (automated driving was realized using the Wizard of Oz technique) when the car exited the automated driving lane, automation failed, or infrastructure was out of order.	State 4	State 1	*	*	*		*	*	*
				*		*				
Gold et al., 2013	The drivers needed to take control to avoid a car accident in two time-to-collision conditions (5 s, 7 s).	State 5	State 1	*		*		*	*	*
Van den Beukel & Van der Voort, 2013	The drivers needed to take control due to an emergency brake of the leading car in three time-to-collision conditions (1.5 s, 2.2 s, 2.8 s).	State 5	State 1			*			*	*
Dogan et al., 2014	The drivers needed to take control of a Traffic Jam Assist system under two conditions: when traffic jam resolved and the speed exceeded 50km/h (anticipated situation) and when drivers were still in a dense traffic jam (unanticipated situation).	State 4	State 1	*		*		*	*	*
Kerschbaum et al., 2014	Drivers were requested to take over approximately 150 m before a construction site, after using a decoupled steering wheel or a coupled steering wheel with hidden spokes.	State 5	State 1	*		*		*	Decoupled	*
								*	Hidden spoke	*
Lorenz et al., 2014	The drivers needed to take control to avoid the sudden car accident in 7 s time-to-collision conditions with heads-up information of a safe corridor or an accident area, in addition to a display icon.	State 5	State 1	Safe corridor		*			*	*
				Accident area		*				
Merat et al., 2014	The automation was disengaged based on time or drivers' gaze allocation (to keep drivers' visual attention on the road). Near the end of the drive, drivers were required to resume control due to a three lane highway reducing to one lane.	State 4	State 1	*					*	*
Naujoks et al., 2014	The drivers needed to take control under three traffic conditions: missing lane markings (easy), lane change (moderate), and high curvature lane (difficult), which automation could not control.	State 4	State 1	*				*	*	
				*		*				
Radlmayr et al., 2014	The drivers needed to take control under four different traffic conditions (in terms of traffic density and driving lane) that automation could not control. Participants performed two different non-driving tasks.	State 5	State 1	*		*			*	*
Telpaz et al., 2015	Five scenarios with different road types (five or two lane road), driving lane, and transition events (static object or slow moving cars) were designed where drivers needed to take back control, to test spatial vibration strategies for a haptic seat.	State 5	State 1	*	*	*			*	*
				*		*				
Zeeb et al., 2015	The drivers needed to take control due to a broken car in front in three time-to-collision conditions (4.9 s, 5.7 s, 6.6 s) with pre-emptive automated deceleration.	State 4	State 1	*		*		*	*	*

Note: (1) "*" means this kind of interface was used during the experiment. (2) Control conditions are not included.

Finally, the effects of the drivers' monitoring level (cf. *alpha* in Fig. 1) on performance after the transition have been studied in experiments where the driving state was State 4 before the transition, that is, in the cases that drivers' monitoring level *alpha* was between 1 and 0 (Dogan, Deborne, Delhomme, Kemeny, & Jonville, 2014; Merat et al., 2014; Zeeb et al., 2015). Dogan et al. (2014) compared driving performance in conditions where transitions could be and could not be anticipated. Merat et al. (2014) added additional systems in the experiment to make sure that the driver was temporarily monitoring and hence did not obtain a monitoring level *alpha* of 0. Specifically, drivers were required to take control when they were looking away from the road for more than 10 s or periodically after every 6 min of automated driving with ACC and LKA. Zeeb et al. (2015) classified drivers into low, medium, and high risk types based on their gaze allocation during automated driving, and their reaction to transitions were compared. In general, these studies concluded that drivers' anticipation of transitions and higher levels of monitoring are beneficial for safety, improving driving performance after the transition. An increase of the monitoring level *alpha*, which leads to improved driver situation awareness, could change a potential AIDC transition to a DIDC transition, and increase the safety on the road. Similarly, Gold, Damböck et al. (2013) proposed a concept for improving transition quality by providing drivers with a monitoring request before the critical event became manifest (i.e., transition steps: State 4 → State 3 → State 1). More generally, research has shown that the adaptive allocation of tasks from automated systems to human operators has a positive effect on the detection of automation failures (e.g., Parasuraman, Mouloua, & Molloy, 1996).

2.5 Discussion

In this paper we described automated driving states (static states and dynamic states) based on the allocation of three primary driving tasks: longitudinal control, lateral control, and monitoring. A transition in automated driving was defined as the process of changing from one driving state to another.

Our concept of driving states differs from the BASt, SAE, and NHTSA levels of automated driving, because these levels of automation describe how the driver and automation *should* drive, whereas our proposed driving states describe what the driver and the automation are doing at a certain moment in terms of longitudinal control, lateral control, and monitoring. By setting the switches, our framework can be used to describe automation that engages temporarily (Fig. 1). Examples are automated lane changes, automated obstacle avoidance,

and AEB. The framework also allows for shared control (dynamic driving states), which according to Mok et al. (2015) "is not classified directly under National Highway Traffic Safety Administration's current Levels of Automation Model" (p. 389). Another limitation of the BASt, SAE, and NHTSA levels is that they conflate expected/required behaviour with actual behaviour. For example, BASt defines highly automated driving as follows: "The system takes over longitudinal and lateral control; the driver is no longer *required* to permanently monitor the system. In case of a take-over request, the driver *must* take-over control with a certain time buffer" (Gasser & Westhoff, 2012; emphasis added). In this definition, which describes a properly functioning system that may be deployed on the roads, it is unclear how to classify a situation where the driver monitors the system but no take-over request is provided due to a technological malfunction or limitation (e.g., a failure to detect an object, resulting in a failure to provide a take-over request), or a situation where the automation produces a take-over request but the driver fails to take over control. An accident with present-day automated driving technology would represent a discrepancy between normative and actual behaviour. According to car manufacturers, drivers should permanently monitor the system and be prepared to take over control at any time, which would classify this as partially automated driving. In reality, however, a driver may not monitor as he should, and therefore is in State 4 as defined in Section 2.2. The BASt, SAE, and NHTSA definitions cannot describe such incidents and accidents. Finally, our approach offers a more fine-grained interpretation than the levels of automation. For example, technologies that offer only lateral automation or only longitudinal automation are classified at the same level of automation in the definitions provided by BASt, SAE, and NHTSA, even though driver's workload and situation awareness are known to be different with lateral automation than with longitudinal automation (Carsten et al., 2012; De Winter et al., 2014; Stanton & Young, 1998; Young & Stanton, 2007).

Note that a temporary interruption of control without changing the actual state is not considered as a transition in our framework. For example, when a driver changes various setpoints during ACC driving without actually turning off the ACC, this would not be regarded as a transition. Furthermore, an attempted but unsuccessful or uncompleted transition does not classify as a transition. In addition, we acknowledge that factors like distraction, fatigue, and drowsiness will lower the driver monitoring level in States 1 and 2. Such unsafe driving states were not explicitly listed in our proposed driving states. However, such states could in principle be added without altering the framework of Figure 1. For

example, one may define a distracted driving state as follows: S_{dx} and S_{dy} are both switched on, S_{ax} and S_{ay} are both switched off, and *alpha* is smaller than 1.

In our framework, we made a distinction between monitoring transitions and control transitions. Monitoring transitions involve changes in the monitoring level of the driver, whereas control transitions involve changes in allocation of control tasks. Three criteria were used to classify transitions of control: 'who initiates the transition?', 'who is in control after transition?' and 'is the transition mandatory or optional?'. Our analysis showed that there are six possible categories of transitions: DIDC mandatory, DIDC optional, DIAC mandatory, DIAC optional, AIDC mandatory, and AIAC mandatory. In addition, we defined DIDC and AIAC transitions as active transitions (self-activation), and DIAC and AIDC transitions as passive transitions (triggered interventions). Lack of preparation for the agent who is in control after passive transitions may lead to unsafe situations. The duration of a transition from initiation to completion, and whether mandatory transitions are time-critical or not, are other important factors that were not explicitly included in our binary classification tree. We acknowledge that time criticality can also be used to classify transitions. However, it is problematic to formally distinguish between time-critical (emergency) and non-time-critical (non-emergency) transitions by means of a clear-cut criterion, because what is considered critical depends on numerous factors such as the specific spatiotemporal relationships of the scenario, the driver's reactions, the road characteristics, visibility, etc.

AIDC transitions have been extensively studied in driving simulator experiments. However, we recommend to not ignore other types of transitions, even if they do not have an obvious relationship with safety. If automation cannot warn the driver about its failure or if the sensors do not detect a road hazard, then a DIDC mandatory transition is the only option to avoid a dangerous situation. Moreover, results from studies on optional DIDC and DIAC transitions in ACC systems may just as well be applicable to automated systems at SAE Levels 3, 4, and 5. A few studies on DIDC transitions have shown that the higher level of automation, the slower the drivers' reaction times (Dambock, Weissgerber, Kienle, & Bengler, 2013; Strand, Nilsson, Karlsson, & Nilsson, 2014), a finding that corresponds to decades of research in psychological vigilance and human-automation interaction (see Cabrall, Happee, & De Winter, 2016; Onnasch et al., 2014, for reviews). However, questions such as 'How long does it take for drivers to detect a failure of an automated driving system?' still remain to be answered (cf. Moray & Rotenberg, 1989).

DIAC and AIAC mandatory transitions may be due to the driver's lack of ability to control the vehicle. The former implies the driver's own awareness of his/her driving inabilities, and the automation needs then to be robust enough to take control when the driver relinquishes control. The latter may involve a driver state monitoring system that diagnoses the driver's abilities. However, the association between psychophysiological measurements and the cognitive state of drivers still needs to be better understood (Whitmore & Reed, 2015). Of course, AIAC transitions can also be implemented in critical-event scenarios irrespective of assessing driver state, such as is currently done in AEB.

Automotive displays have undergone various refinements in the last decades (Akamatsu, Green, & Bengler, 2013), but their design may need to change significantly in order to inform drivers about both the transitions and automation status. As discussed in Section 4.2, the signal for getting the driver into the driving State 3 or lower is typically a visual, vocal, acoustic, or tactile warning (or combinations of these). Because of the diverse designs, research questions, and lack of detailed information, questions like 'which method is more effective?' or 'what settings should be used for the interface?' need to be further elaborated. It has been argued that take-over requests should be multimodal rather than unimodal, because different sensory modalities can complement each other (Petermeijer et al., 2016). For example, a vibrotactile warning in the driver's seat can be a useful alerting device when a person is visually distracted or engaging on a conversation, while auditory feedback is preferred to vibrotactile feedback when the driver is driving on an uneven road, wears thick clothing, or is not in permanent contact with the seat.

Previous research has investigated whether transition quality can be improved by means of applying intermediate states. For instance, systems that encourage monitoring before a transition (e.g., State 4 → State 3 → State 1) or which deactivate the longitudinal or lateral control tasks in sequence (State 5 → State 2 → State 1) have been designed (De Vos et al., 1997; Gold, Lorenz et al., 2013; Willemsen et al., 2014), but the evaluated systems were not found to significantly improve driving performance or comfort. Dynamic driving states (shared control)—defined as a situation where human and automation are carrying out tasks simultaneously—may facilitate smooth control transitions (Inagaki, 2003; Sheridan, 2011). Control systems need to be integrated with manual/biomechanical control models describing how driver steer, brake, and accelerate during transitions, in order to understand the pros and cons of discrete versus continuous transitions. Nilsson, Strand, Falcone, and Vinter (2013) found that when drivers encounter an automation failure, they were more likely to steer than

to apply the brakes. Similarly, driving simulator research by Levitan et al. (1998) found that drivers preferred to take over control from automation by first steering and then using the accelerator, instead of vice versa. Thus, the development of HMIs and control algorithms for safely transferring control between automation and drivers is a challenge for human factors researchers in automated driving.

A final consideration, which was not explicitly included in our framework, is that of adaptive automation. Previous research has demonstrated that adaptively allocating the control task between humans and automation can be beneficial for effective human-machine interaction (Hancock et al., 2013; Kaber & Endsley, 2004; Parasuraman et al., 1996). For this purpose, one may need to create a switching agent that allocates tasks to the driver and/or the automation and that can determine whether transitions should happen. Recently, Baltzer et al. (2014) built a prototype of their Mode Selection and Arbitration Unit (MSAU), which distributed responsibility and control between the automation and the driver. The ideal design of the switching agent should not only consider the conditions of the environment and automation, but should also have knowledge of the states, habits, and experience level of the driver (e.g., Beggiato, Pereira, Petzoldt, & Krems, 2015; Whitmore & Reed, 2015). For example, as Larsson, Kircher, and Hultgren (2014) showed, when drivers get accustomed to ACC, they become more aware of the system's limitations and respond quicker to emergency situations. Klein (2008) argued that humans tend to execute actions they have experienced before, instead of acting optimally in time-limited tasks. This advocates for an automatic switching agent as opposed to a human one. Furthermore, through training and experience, drivers can learn to work around automation problems.

2.6 Conclusion

In summary, this paper defines the different driving states from a descriptive (i.e., not a normative) function allocation perspective taken at the level of a joint team of both driver and automation. In turn, transitions in automated driving are defined based on the proposed driving states. Our spectrum also clarifies and incorporates the concept of both control transitions and monitoring transitions. Moreover, we propose a classification tree that distinguishes six possible types of transitions, and we provide use cases for these transition types. By using the elements of the initiation entity and the resultant control entity of actual transitions, and by distinguishing between active and passive transitions, we assessed the safety criticality of each of the transition type. All of the above aspects taken together should

support automated driving research and development as well as problem/solution design space explorations that go beyond the classic 'take-over' (AIDC) scenario.

Case in point, we applied the proposed framework to review the literature on experimental research of transitions in automated driving, and accordingly to identify convergent and divergent results and gaps in the literature. We believe that our framework can contribute to a fruitful and productive dialogue among researchers on the topic of transitions in automated driving. This paper also reminds us that human factors engineering is crucial when introducing automation to a human-machine system (and see Bainbridge, 1983; Parasuraman & Riley, 1997; Sheridan & Parasuraman, 2005). Until the driving task is wholly automated under all possible circumstances and humans are prohibited from driving manually (e.g., because the automated car does not have a steering wheel anymore), transitions between the driver and the automation will remain a key element of automated driving.

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CHAPTER 3

HOW MUCH TIME DO DRIVERS NEED TO OBTAIN SITUATION AWARENESS? A LABORATORY-BASED STUDY OF AUTOMATED DRIVING

Abstract

Drivers of automated cars may occasionally need to take back manual control after a period of inattentiveness. At present, it is unknown how long it takes to build up situation awareness of a traffic situation. In this study, 34 participants were presented with animated video clips of traffic situations on a three-lane road, from an ego-centric viewpoint on a monitor equipped with an eye tracker. Each participant viewed 24 videos of different durations (1, 3, 7, 9, 12, or 20 s). After each video, participants reproduced the end of the video by placing cars in a top-down view, and indicated the relative speeds of the placed cars with respect to the ego-vehicle. Results showed that the longer the video length, the lower the absolute error of the number of placed cars, the lower the total distance error between the placed cars and actual cars, and the lower the geometric difference between the placed cars and the actual cars. These effects appeared to be saturated at video lengths of 7 to 12 s. The total speed error between placed and actual cars also reduced with video length, but showed no saturation up to 20 s. Glance frequencies to the mirrors decreased with observation time, which is consistent with the notion that participants first estimated the spatial pattern of cars after which they directed their attention to individual cars. In conclusion, observers are able to quickly reproduce the layout of a situation, but the assessment of relative speeds takes 20 s or more.

3.1   Introduction

Over the past few decades, an increasing number of automated driving systems have become available, both for research and consumer purposes. Automated driving systems in which the driver can opt to be 'out-of-the-loop' by engaging in non-driving tasks such as reading or resting are expected within a decade (Kyriakidis et al., 2015; Underwood, 2014). When the automation malfunctions or reaches its functional limits, control has to be handed back to the driver. In such cases, the automation typically issues a warning signal (also called a take-over request, see Lu et al., 2016 for a review) after which the driver has to resume the driving task (SAE International, 2014).

A critical design parameter in the development of an automated driving system is the available time for taking over control, sometimes referred to as 'lead time', 'time buffer', or 'time budget' (Gasser & Westhoff, 2012; SAE International, 2014; Zeeb et al., 2016). If drivers do not have sufficient time to assess the situation prior to taking control, an accident may result (Mok et al., 2015). Drivers may prefer long lead times to prepare for the upcoming transition of control, but in reality, this is not always technologically feasible. For example, limitations in sensors (e.g., the limited range of a forward-facing radar) pose barriers regarding the maximum lead time that is feasible. In summary, it is important to understand how much time drivers need to gain situation awareness (SA), because this sets demands on the automated driving technology.

Various studies have previously examined the effects of lead time on drivers' behaviour after resuming control (Clark & Feng, 2015; Gold et al., 2013; Mok et al., 2015). For example, a driving simulator study by Gold et al. (2013) found that the less time is available until colliding with a stationary object (5 s vs. 7 s), the more abrupt are the drivers' braking and steering inputs after receiving a take-over request. This study reported an average gaze reaction time (i.e., the time between the take-over request and the eye-gaze moving away from the non-driving task) of 0.5 s, an average hands-on-steering-wheel time of 1.5 s, and an average mirror-scan time of about 3 s (for similar results see Kerschbaum et al., 2015). Van den Beukel and Van der Voort (2013) found a decrease in the number of accidents and higher self-reported SA scores when more time was available. Mok et al. (2015) found that only few participants in a 2 s lead-time condition safely negotiated a hazardous situation, while the 5 s and 8 s conditions yielded considerably safer driver behaviours. A driving simulator study by Samuel et al. (2016) compared 4, 6, 8, and 12 s lead times, and found that participants needed

a lead time of at least 8 s in order to detect a latent pedestrian hazard with the same accuracy as they did when being in control of the vehicle. Driving simulator research by Merat, Jamson, Lai, Daly and Carsten (2014) and by Desmond, Hancock, and Monette (1998) suggests that it may take up to 20 s or 40 s before vehicle control is fully stabilised after reclaiming control. Although the above studies provide valuable knowledge, they do not offer much insight into the cognitive processes of how drivers are able to build SA of a traffic situation as a function of the available time.

Over the last 25 years, the topic of SA has been extensively investigated (Endsley, 2015). The Situation Awareness Global Assessment Technique (SAGAT) is one of the standard instruments for measuring SA (Garland & Endsley, 1995). In this method, the screens of a simulator are temporarily blanked, and participants subsequently have to answer queries about objects and unfolding events in the simulation. Although SAGAT has been criticized for the fact that it measures SA intermittently rather than continuously, and for relying heavily on memory skills (for discussion see Durso et al., 2006; Gutzwiller & Clegg, 2013; Stanton et al., 2015), there is now a sound body of literature showing that SAGAT scores exhibit criterion validity with respect to task performance (Durso et al., 1995; Gardner et al., 2015; Loft et al., 2015; Salmon et al., 2009). Various promising alternative methods have been proposed for measuring SA, such as real-time probing (e.g., Loft et al., 2013; Martelaro et al., 2015; Pierce, 2012) and physiological techniques (e.g., Crundall et al., 2003; Gugerty, 2011), but at present SAGAT still appears to be the most widely applied and validated SA assessment tool (see also Endsley, 2000; 2015).

The answer categories in SAGAT are usually discrete or discretised values of the state of the virtual environment (e.g., Salmon et al., 2006; Loft et al., 2015). Gugerty (1997) used a similar technique as SAGAT for measuring participants' dynamic spatial memory by means of continuous values. Specifically, participants watched animations of traffic situations that lasted 18 to 35 seconds, and after each video, they indicated the positions of surrounding cars from a top-down view. Participants' level of SA was operationalized by comparing the positions of the placed cars with the actual positions of the cars in the animation. Gugerty found that the more cars are to be recalled, the poorer the performance on the SA task. Furthermore, he found that when the number of cars was larger, participants showed a prioritization effect whereby the most hazardous cars were remembered best.

In the present research, we refined the method used by Gugerty (1997) for determining the effect of time on SA scores. Specifically, we investigated the effect of viewing time (i.e.,

video length) with two levels of traffic density, namely 4 or 6 cars in surrounding traffic. The use of 4 and 6 cars is in approximate agreement with Pylyshyn and Storm (1988), who found that people can track up to five moving objects in a perceptual task, and with Gugerty (1997) who used 3 to 8 cars in his research. In our study, six different video lengths were adopted, ranging between 1 s and 20 s. The video lengths were based partly on a pilot study conducted prior to the present study (Coster, 2015). In this pilot, seven participants watched videos of animated traffic scenes and pressed the spacebar when they had assessed the situation to such an extent that they would feel safe to take over control. The results showed that a viewing time of 12 s was generally deemed sufficient, with an overall minimum of 3 s. In visual processing research, it has been found that participants can recognize the gist of a scene when having viewed it for only 20 ms (Thorpe et al., 1996). Oestmann et al. (1988) found that radiologists were able to detect 'subtle cancers' and 'obvious cancers' from a radiograph in 0.25 s with true positive rates of 30% and 70%, respectively (cf. 74% and 98%, respectively, for unlimited viewing times). However, sub-second viewing times are probably too short for processing dynamic traffic scenes that require visual search by means of multiple fixations and saccades (see Rayner, 2009 for a review on eye movements and visual search). Lead times that are typically used in driving simulator research range between 2 s and 12 s (Gold et al., 2013; Körber et al., 2015, 2016; Melcher et al., 2015; Mok et al., 2015; Samuel et al., 2016). In summary, our range of video lengths encompasses lead times that are commonly used, and range from extremely short (1 s) to longer than has been studied before (20 s).

The dependent measures in this study were: (1) self-reported task difficulty and time sufficiency, (2) the absolute error between the number of placed cars and the actual number of cars, (3) the error between the positions and indicated speeds of the placed cars relative to the actual positions/speeds of the cars, making use of an algorithm that globally selects a match between placed and actual cars by minimizing the positional difference, (4) the geometric difference between the positions of the placed and actual cars, and (5) eye-gaze activity. We expected that when the viewing time is longer, participants would find the task easier and have a better reproduction performance. Our corresponding aim was to explore at which video length these effects would saturate.

The geometric difference method is an innovation in SA assessment. It is based on a method for comparing polygons previously introduced by Arkin et al. (1991), which was said to be "invariant under translation, rotation, and change of scale, reasonably easy to compute, and intuitive" (p. 209). We applied this technique to obtain a generic index of difference that

avoids the use of arbitrary parameters, such as correction factors related to the fact that people have a tendency to underestimate the distance to objects in virtual environments.

Eye tracking is widely used in studies of hazard perception, a term often equated with SA (Horswill & McKenna, 2004; Hosking et al., 2010; Underwood et al., 2002; Underwood et al., 2013). We used eye tracking to gain a deeper understanding of how participants build SA as a function of time. It is well known that eye movements are correlated with bottom-up and top-down attention (Borji & Itti, 2013; Henderson, 2003; Itti & Koch, 2001) and memory of visual objects (Irwin & Zelinsky, 2002; Moore & Gugerty, 2010). For example, using a SAGAT method, Moore and Gugerty (2010) found that the more participants fixated on an aircraft in an air traffic control task, the higher their SA (i.e., responses to state queries) for that aircraft. Unema et al. (2005) and Over et al. (2007) found that in visual search tasks, participants exhibit a coarse-to-fine eye-movement strategy, whereby the first fixations and saccades had a short duration and large amplitude, respectively, and later fixations became longer-lasting with smaller-amplitude saccades in between the fixations. In this paper, we measured whether participants glanced at the road or at the mirrors, and how frequently they glanced at the mirrors, as a function of observation time. We explored whether these measures of attention distribution and glance frequency exhibit similar saturation profiles as the objective task scores.

3.2 Method

3.2.1 Hardware

The videos and graphical user interface (GUI) were presented on a 24-inch widescreen HD monitor of the SmartEye DR120 remote eye tracking system. The videos were programmed using PreScan 7.0 (Tass International, 2015) and had a resolution of 1920 x 1080 pixels. The participants reproduced the traffic situations using a standard Dell mouse.

3.2.2 Videos

Each video began with a 5 s crosshair display for participants to focus on, after which the traffic situation from an ego-centric viewpoint was presented for 1, 3, 7, 9, 12, or 20 s. At the end of the video, a black screen was displayed for 0.5 s. The rear view mirror and left wing mirror were positioned in such a way as to resemble real positions. Due to geometric

constraints, this was not possible for the right wing mirror, which was therefore placed at the right edge of the video (Figure 1).

Figure 1. Screenshot of a video that includes six surrounding cars.

In real driving, sound cues may aid in the formation of SA. For example, a driver may infer the location and speed of a nearby car through the sounds of that car's engine and tires. In our study, we decided to eliminate sound cues and make the SA task visual-only. Therefore, during each video, a standard sound of driving on a highway was played that was unrelated to the traffic in the video.

3.2.3 Participants

Thirty-four participants (5 female, 29 male) with a valid driver's license, aged between 20 and 31 years ($M = 24.6$, $SD = 2.6$ years) participated in this study. The mean participants' age when obtaining the first driver's license was 19.2 years ($SD = 2.4$), and the mean number of years of licensure (i.e., current age minus the age when obtaining the first driver's license) was 5.41 years ($SD = 2.92$). On a scale of 0 (every day), 1 (4–6 days a week), 2 (1–3 days a week), 3 (once a month to once a week), 4 (less than once a month), and 5 (never), the mean answer to "On average, how often did you drive a car or motorcycle during the last 12 months?" was 2.62 ($SD = 1.04$, min = 0, max = 4). Furthermore, on a scale from 0 (0 km), 1 (1–1000 km), 2 (1,001–5000 km), 3 (5,001–10,000 km), 4 (10,000–15,000 km) to 10 (more

than 100,000 km), the answer to "About how many kilometres did you drive during the last 12 months?" was on average 2.59 ($SD = 1.79$, min = 1, max = 9).

All participants read and signed a consent form, explaining the purpose and procedures of the experiment. Participants received €5 for their participation. They were split into two groups based on their recruitment number (i.e., group A if the participant number was odd, and group B if it was even). These two groups viewed 24 test videos, whereby each video in one group maps to a video in the other group, with these videos featuring the same traffic and the same ending moment, but a different starting moment. Both groups consisted of 17 participants: 3 females, 14 males, aged between 21 and 31 ($M = 25.0$, $SD = 2.8$ years) for group A; 2 females, 15 males, aged between 20 and 29 ($M = 24.2$, $SD = 2.4$ years) for group B. The mean number of years of licensure was 5.65 ($SD = 3.32$) and 5.18 ($SD = 2.56$) for groups A and B, respectively. For groups A and B, the mean driving frequency on the scale from 0 to 5 was 2.88 ($SD = 0.93$) and 2.35 ($SD = 1.69$), respectively, and the mean mileage on the scale from 0 to 10 was 2.35 ($SD = 1.14$) and 2.82 ($SD = 1.91$), respectively. According to an independent-samples t test, groups A and B were not statistically significantly different with regard to age, gender, license age, years of licensure, driving frequency, and mileage (p = .361, .641, .672, .646, .142, & .453, respectively).

3.2.4 Situations

Participants viewed videos of traffic situations on a three-lane highway, on which the ego-vehicle was driving in the middle lane with a constant speed of 28 m/s. The training videos lasted 12 s and featured three cars of surrounding traffic, whereas the test videos incorporated four or six surrounding cars. Both traffic densities were used 12 times. The test videos lasted 1, 3, 7, 9, 12 or 20 s.

Each video length occurred twice per traffic density and four times in 24 test videos. The test videos were shown to each participant in randomized order.

All traffic in each video met the following criteria. Each car was

- within a range of 80 m behind to 120 m ahead of the ego-vehicle during the full length of the video.
- visible during the full length of the video, except when driving through the blind spot. This visibility criterion had the effect that there could be only one car directly in front of and/or behind the ego-vehicle on the middle lane.

- starting and ending outside of the blind spot.

- driving at one of five constant speeds: 25.5, 26.75, 28, 29.25 or 30.5 m/s.

- staying in its own lane during the full length of the video.

- at least 5 m in front of or behind other cars at all times.

The model and colour of each car were randomly assigned out of 13 possible colours and 10 possible models. Averaged across the 24 scenarios, 57% of the cars were in front of the ego-vehicle at the end of the scenarios (58% at the beginning of the scenarios). In groups A and B, an overtaking event of the ego-vehicle occurred in 6 and 8 of the 24 scenarios, respectively.

3.2.5 Procedure

Prior to the test, the participants filled out a questionnaire about their driving experience. Participants were asked to adjust the chair in order to face the monitor mid-front, with the hind legs of the chair within a demarcation on the floor, approximately 65 cm away from the monitor. The height of the monitor was adjusted to the participant's height, after which the eye tracker was calibrated. Participants were given 2 training trials, followed by 24 test trials, viewing videos of traffic situations on a three-lane highway. After each video, participants reproduced the final positions of the surrounding cars by placing a minimum of 1 and a maximum of 8 vehicles without time restriction. Participants also indicated the speeds of the placed cars in relation to the ego-vehicle (Figure 2).

After reproducing a situation, a two-item questionnaire measured the subjective task difficulty ('The task was difficult') and time sufficiency ('I had sufficient time to perform the task') on a scale from 0 (completely disagree) to 100 (completely agree). Participants received oral instructions during the training trials about (1) how to place the cars and use the slider bars, (2) how to interpret the time sufficiency question as 'the video was long enough for me to perform the task', and (3) that surrounding traffic would not necessarily follow traffic rules (e.g., cars could overtake on the right). The traffic was not constrained by traffic rules, because we wanted to retain symmetry in the videos by letting all cars drive with constant speeds without changing lanes. For example, when preventing the traffic from overtaking the participant on the right, the mean speed on the left lane would be higher than the mean speed on the right lane. Such asymmetric videos would have complicated the analyses and interpretation of how well participants were able to place cars.

After each trial, the placed cars and the actual cars were shown side by side in two top-down views, providing feedback to the participant. This feedback was provided to enhance participants' engagement in the task, and to prevent misunderstandings and biases that may occur when participants have to map the three-dimensional video to a two-dimensional representation. The duration of the experiment was approximately 60 minutes including preparation time.
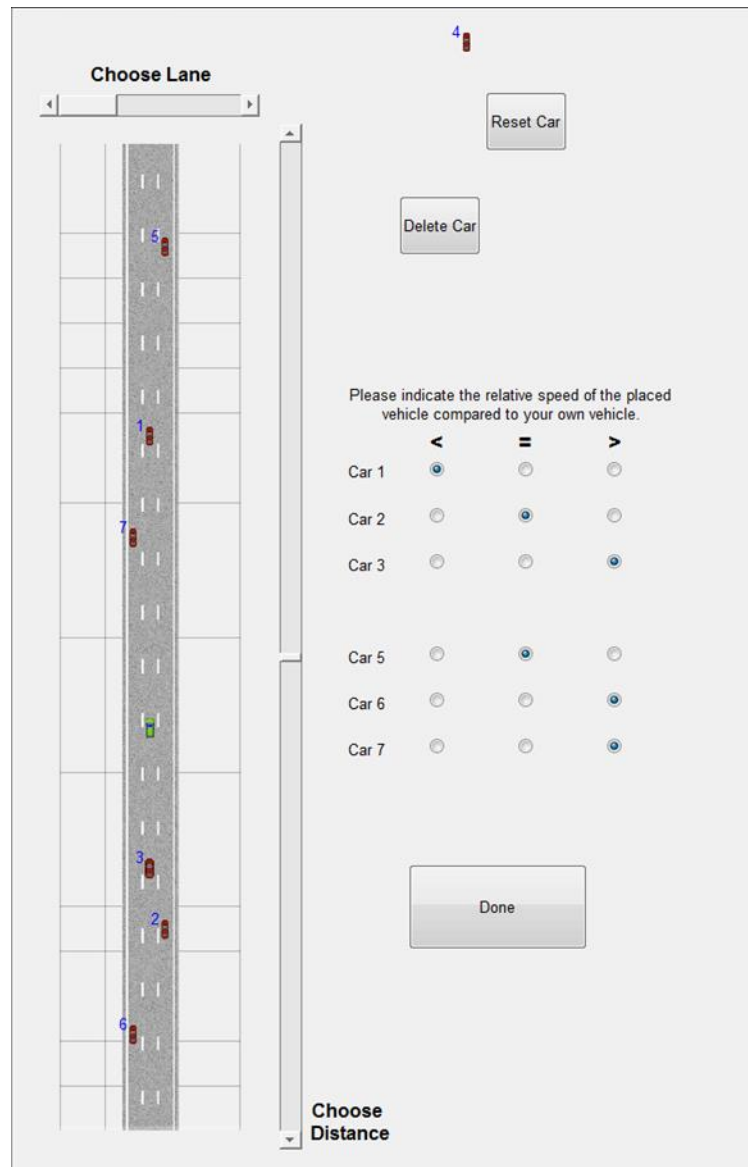
Figure 2. Reproduction of a traffic situation. Red cars represent the surrounding cars. The green car represents the ego-vehicle. The slider bars were used to set the positions of surrounding vehicles. The radio buttons were used to indicate the relative speed. Placed cars could be deleted by pressing the 'Delete Car' button, and deleted cars could be placed again by pressing the 'Reset Car' button. Additional cars could be placed by pressing the 'New Car' button (only visible when no cars were deleted). The 'Done' button was pressed when a participant had finished the reproduction.

3.2.6 Dependent Measures

The following dependent measures were used:

1. Self-reported time sufficiency (%)

2. Self-reported task difficulty (%)

3. Absolute error of the number of placed cars, defined as the absolute error of the number of placed cars, calculated according to Eq. 1, where np is the number of cars that were placed and n_a is the actual number of cars in the video.

$$S_1 = \left| n_p - n_a \right| \tag{1}$$

4. *Total distance error between the placed cars and actual cars.* First, the placed and actual cars were matched to each other. A particular combination of matches $c_\alpha(m_1, m_2, ..., m_{\max(n_p, n_a)})$ connects placed and actual cars, where a match m is between a placed car and an actual car. The number of possible combinations $N(c)$ of matches between placed and actual cars is given according to Eq. 2.

$$N(c) = S(\max(n_p, n_a), \min(n_p, n_a)) \min(n_p, n_a)! \tag{2}$$

where $S(n,k)$ is the Stirling number of the second kind. For example, if $n_p = 6$ and $n_a = 6$, then $N(c) = 720$, if $n_p = 5$ and $n_a = 6$, then $N(c) = 1,800$, and if $n_p = 6$ and $n_a = 4$, then $N(c) = 1,560$. If one placed car $p(i) = \left(p_{i,x}, p_{i,y}, p_{i,v} \right)$ and one actual car $a(j) = \left(a_{j,x}, a_{j,y}, a_{j,v} \right)$ are matched, the distance error and speed error between these two cars are given by Eq. 3 and 4, respectively

$$dE(m(p(i), a(j))) = \sqrt{(p_{i,x} - a_{j,x})^2 + (p_{i,y} - a_{j,y})^2} \tag{3}$$

$$sE(m(p(i), a(j))) = \left| p_{i,v} - a_{j,v} \right| \tag{4}$$

Here, $\left(p_{i,x}, p_{i,y} \right)$ and $\left(a_{j,x}, a_{j,y} \right)$ are the lateral and longitudinal positions of the placed car p_i and actual car a_j, where the centre of the ego-vehicle is the coordinate origin. $p_{i,v}$ and $a_{j,v}$ are the speeds of the placed car p_i and actual car a_j, respectively. For both the placed car p_i and actual car a_j, $p_{i,v}$ and $a_{j,v}$ are equal to −1, 0, or +1, when their speeds are slower than, equal to, or faster than the ego-vehicle, respectively.

The total distance error of one combination of matches is

$$DE(c_\alpha) = \sum_{k=1}^{\max(N_p, N_a)} \left(dE(m_k)\big|_{m_k \in c_\alpha} \right) \tag{5}$$

The total distance error is $DE(c_{\min})$, where $c_{\min}$ is the combination that gives the minimal distance among all $N(c)$ combinations (Eq. 6)

$$DE(c_{\min}) = \min\{DE(c_1), DE(c_2), ..., DE(c_{N(C)})\} \tag{6}$$

5. *Total speed error*. This measure is calculated based on the minimal distance for combination match $c_{\min}(m_1, m_2, ..., m_{\max(n_p, n_a)})$ (Eq. 7)

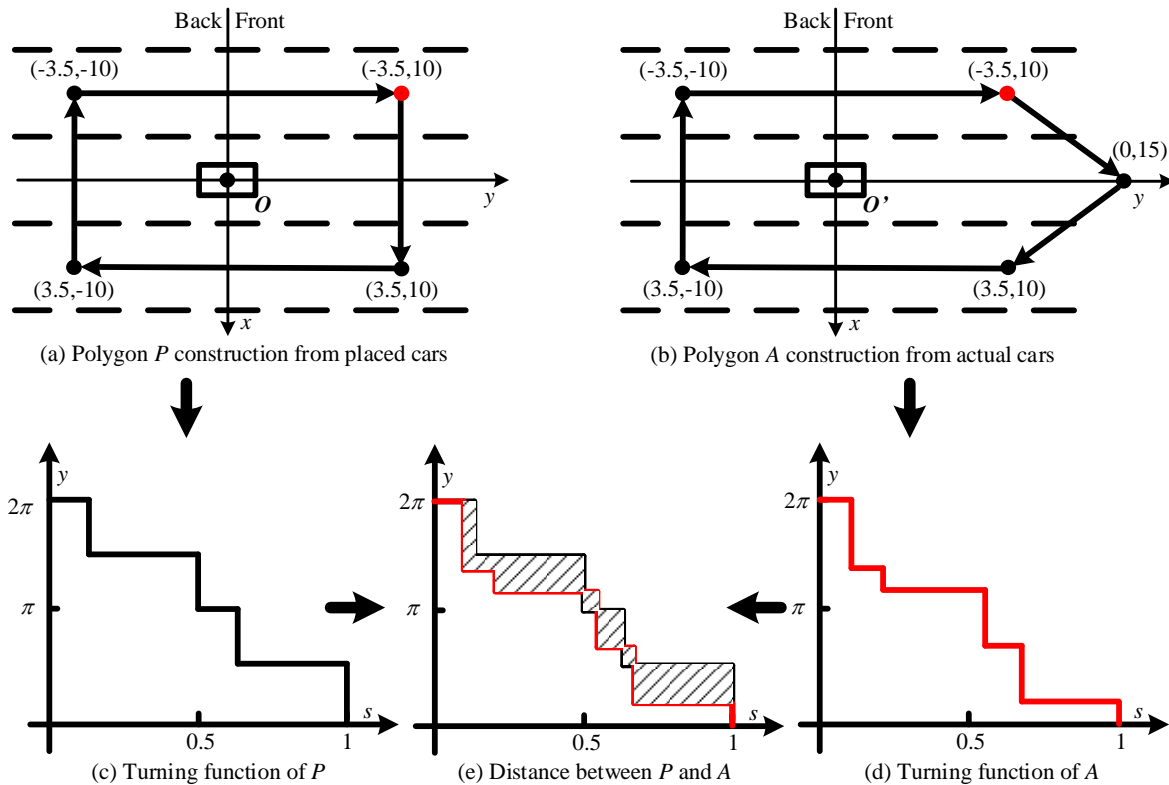$$SE(c_{\min}) = \sum_{k=1}^{\max(N_p, N_a)} \left(sE(m_k)\big|_{m_k \in c_{\min}} \right) \tag{7}$$

6. *Geometric difference.* The turning function algorithm (Arkin et al., 1991) is widely used in computer vision to calculate the difference between two polygons. It maps a two-dimensional shape to a one-dimensional function. The first step is to construct polygons that represent the positions of placed and actual cars. Figure 3a provides an example of P with all its nodes, where each node represents the centre of the placed car pi. The following 10 possible nodes can be used to construct P:

1) $(-3.5, \min(p_{i,y}\big|_{p_{i,y}>0 \cap p_{i,x}=-3.5}))$ 2) $(-3.5, \max(p_{i,y}\big|_{p_{i,y}>0 \cap p_{i,x}=-3.5})$

3) $(0, \max(p_{i,y}\big|_{p_{i,y}>0 \cap p_{i,x}=0}))$ 4) $(0, \min(p_{i,y}\big|_{p_{i,y}>0 \cap p_{i,x}=0}))$

5) $(3.5, \max(p_{i,y}\big|_{p_{i,x}=3.5}))$ 6) $(3.5, \min(p_{i,y}\big|_{p_{i,x}=3.5}))$

7) $(0, \min(p_{i,y}\big|_{p_{i,y}<0 \cap p_{i,x}=0}))$ 8) $(0, \max(p_{i,y}\big|_{p_{i,y}<0 \cap p_{i,x}=0}))$

9) $(-3.5, \min(p_{i,y}\big|_{p_{i,y}<0 \cap p_{i,x}=-3.5}))$ 10) $(-3.5, \max(p_{i,y}\big|_{p_{i,y}<0 \cap p_{i,x}=-3.5}))$.

The polygon is constructed with a sequence from node 1 to 10. A node can be skipped if it does not exist, or if it is the same node as a neighbouring node in front. The same process is applied to the actual cars a_i that compose polygon A (Figure 3b). The second step is to represent the polygon as a turning function. As illustrated in Figure 3c, the turning function measures the external angle of the clockwise tangent as a function of the arc-length s from the starting node of P. The function decreases with right-hand

turns and increases with left-hand turns. The perimeter length is scaled to 1 to make a comparison possible. The function always starts at $(0, 2\pi)$ and always ends at $(1, 0)$. Figure 3d shows the turning function for *A*. The third and final step is to calculate the distance between the two turning functions (Eq. 8, Figure 3e).

$$L(P,A) = \int_0^1 |T_P(s) - T_A(s)| ds \tag{8}$$

(a) Polygon *P* construction from placed cars

(b) Polygon *A* construction from actual cars

(c) Turning function of *P*

(e) Distance between *P* and *A*

(d) Turning function of *A*

Figure 3. Procedure to determine the geometric difference between actual and placed cars. The lane width was 3.5 m.

3.2.7 Eye-tracking Analysis

Participants' eye movements were analysed in order to understand how participants distributed their attention while watching the video. Four equally sized rectangular areas were defined, namely (1) road centre, (2) rear view mirror, (3) left wing mirror, and (4) right wing mirror. We defined the net dwell time percentage across all situations of all participants, as a function of observation time in bins of 1 s. Furthermore, in order to obtain a measure of visual search and gaze activity, we measured how often per second participants glanced at one of the three mirrors. For this latter analysis, a glance was counted if the dwell time to the mirror was at least 200 ms. This 200 ms threshold corresponds to typical measures of fixation duration

(e.g., Velichkovsky et al., 2002). Note that our SmartEye eye-tracker did not have the precision and accuracy to be able to distinguish between cars within an area of interest (see Funke et al., 2016 for an assessment of eye trackers).

3.2.8   Statistical Analyses

Three types of statistical analyses were conducted. First, a one-way repeated measures ANOVA after rank-transformation was performed (Conover & Iman, 1981), with the video length as the repeated-measures factor. Pairwise comparisons between video lengths were conducted by means of paired-samples t tests followed by a Bonferroni correction, which effectively means that the significance level (α) was set to 0.00333 (= 0.05 /15). Effect sizes for the pairwise comparisons were expressed in terms of Cohen's d_z for assessing within-subject effects (Faul et al., 2007).

Second, we performed a between-subjects comparison between the participants in group A versus the participants in group B. These two groups had viewed the same videos with the same endpoint; only the video length was different. We assessed in how many of the 24 situations the longer videos yielded higher scores on the dependent measures than the shorter videos.

Third, at the level of the 24 situations, we assessed Spearman rank-order correlations between video length and the scores on the dependent measures. An objective measure of task difficulty, defined as the distance from the ego-vehicle to the actual car summed across all 4 or 6 cars, was partialled out in order to determine whether the effects between video length and task performance were robust to situation-specific effects.

3.3   Results

Some data had to be excluded due to quality issues, see Table 1 for an overview. A small number of trials were excluded due to technical malfunctions (e.g., video not shown, data storage error) or because the participant initially misunderstood the task. The data for two participants were excluded entirely because the experimenter's log files revealed that they had used mnemonics (hands, fingers) to enhance their task performance. Moreover, for the eye-tracking analysis, data could be used from 21 out of 34 participants.

Figures 4–9 show the results for the self-reported time sufficiency, self-reported difficulty, mean absolute error of the number of placed cars, mean total distance error, mean total speed

error, and the mean geometric difference score, respectively, for each of the 24 videos. The means of group A and group B are connected by a line.

Table 1. Overview of excluded trials, number of participants for which trials were excluded, and types of data that were excluded.

Malfunction / behaviour / limited conditions	Number of participants for which data were excluded	Total number of erroneous trials	Data not included for erroneous trials
Used hands / fingers as memory support	2	2*24	Reconstruction data, and self-report data
Video malfunction (video did not show)	1	1	
Data storage error	6	6	Reconstruction data
Misunderstanding of GUI controls	1	1	Reconstruction data and self-report data
Reconstructed beginning (instead of ending) of the video	2	5	
Accidentally pressed 'Done' button	1	1	
Misunderstood the meaning of 'time sufficiency'	1	24	Self-report data of the 'time sufficiency question'
Did not answer the two questions	1	24	Self-report data
Participant wore glasses, Software crashed, tracking/calibration problems	13	13*24	Eye-tracking data

*Note*. Reconstruction data encompasses positions and speeds of placed cars.

3.3.1 Subjective measures

Self-reported time sufficiency and self-reported difficulty showed consistent effects of video length (Figures 4 and 5). The pairwise comparisons between video lengths indicate that self-reported time sufficiency has statistically significant effects for almost all pairs of video lengths (Table 2), with an improvement even from 12 s to 20 s videos. The effects were less strong for task difficulty than for time sufficiency (Table 2).

3.3.2 Tasks performance measures

Task performance in terms of the error in the number of placed cars (Figure 6) and the total distance error (Figure 7) shows a clear improvement with video length. In 20/21 of the 24 group A versus group B comparisons, the longer videos featured better task performance (Table 2). However, there appears to be a saturation effect of video length, whereby for the error in the number of placed cars there was no statistically significant difference anymore between 7 s and 20 s videos. Similarly, for the total distance error, there was no significant difference between 12 s and 20 s videos.
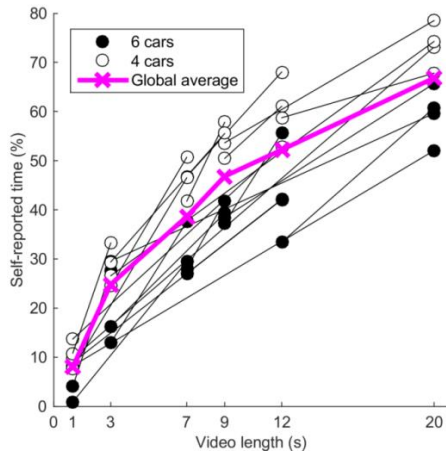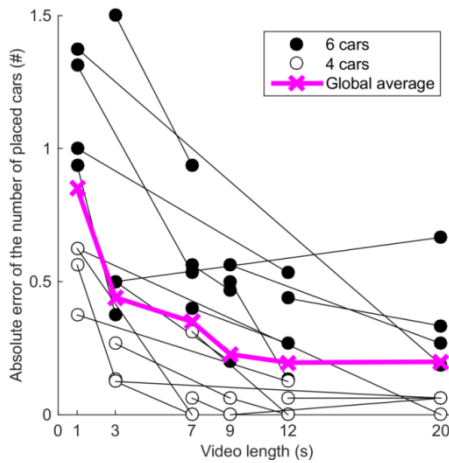
Figure 4. Mean self-reported time sufficiency across the participants, for each of the 24 situations. The A and B groups are connected by a line.
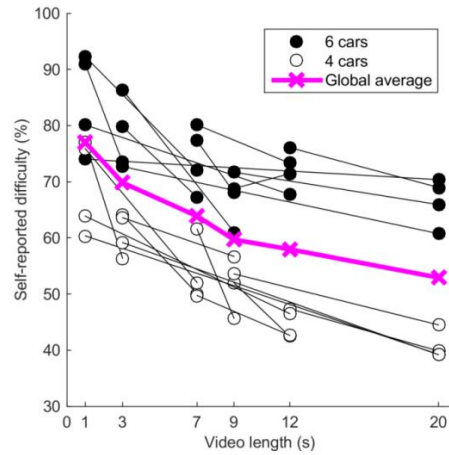
Figure 5. Mean self-reported difficulty across the participants, for each of the 24 situations. The A and B groups are connected by a line.

Figure 6. Mean absolute error of the number of placed cars, for each of the 24 situations. The A and B groups are connected by a line.
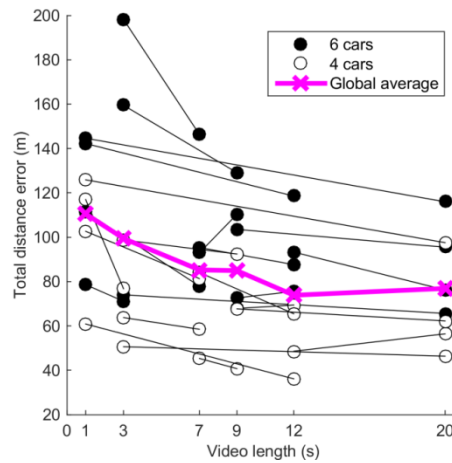
Figure 7. Mean total distance error, for each of the 24 situations. The A and B groups are connected by a line.
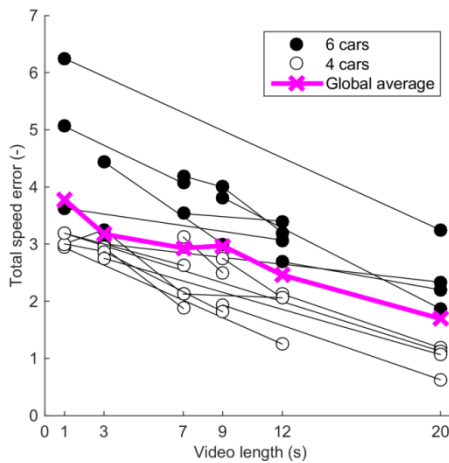
Figure 8. Mean total speed error, for each of the 24 situations. The A and B groups are connected by a line.
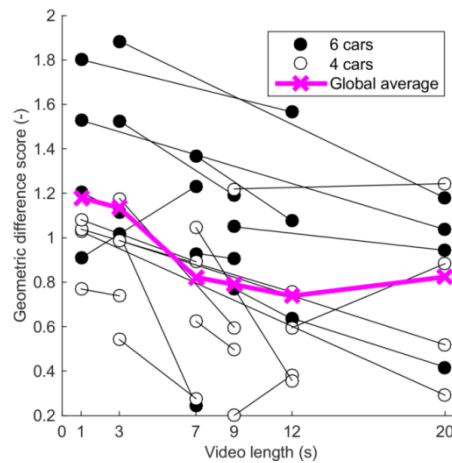
Figure 9. Mean geometric difference score, for each of the 24 situations. The A and B groups are connected by a line.

Table 2. Result of the repeated measures ANOVA, and effect sizes (d_z) of paired comparisons between video lengths.

Measure	df	F^a	η^2	1 vs. 3	1 vs. 7	1 vs. 9	1 vs. 12	1 vs. 20	3 vs. 7	3 vs. 9	3 vs. 12	3 vs. 20	7 vs. 9	7 vs. 12	7 vs. 20	9 vs. 12	9 vs. 20	12 vs. 20	A vs. B Comp^b
Time sufficiency	5,145	146.4	.835	**-1.69**	**-2.41**	**-2.35**	**-2.95**	**-4.93**	**-1.04**	**-1.44**	**-1.82**	**-3.01**	**-0.65**	**-1.27**	**-2.91**	-0.48	**-1.39**	**-1.07**	24
Difficulty	5,150	24.9	.454	0.56	**0.95**	**1.12**	**1.32**	**1.33**	0.51	**0.87**	**0.90**	**1.03**	0.34	**0.65**	**0.79**	0.26	0.45	0.33	1
Error in the number of placed cars	5,155	20.5	.398	**0.68**	**0.96**	**1.37**	**1.54**	**1.58**	0.11	0.54	**0.67**	**0.69**	0.44	**0.59**	0.54	0.15	0.09	-0.07	3
Total distance error	5,155	11.4	.269	0.39	**0.88**	**0.95**	**1.46**	**1.19**	0.16	0.18	**0.58**	0.52	0.05	**0.58**	0.36	0.60	0.32	-0.19	4
Total speed error	5,155	30.9	.499	0.55	**0.74**	**0.74**	**1.38**	**2.40**	0.26	0.19	**0.66**	**1.69**	-0.03	0.56	**1.47**	0.49	**1.43**	**0.78**	1
Geometric difference	5,155	6.8	.181	-0.01	0.45	**0.74**	**0.61**	0.51	**0.56**	**0.71**	**0.76**	**0.66**	0.12	0.20	0.04	0.10	-0.06	-0.15	4

Note. Boldface = the effect between these two video lengths was statistically significant according to a paired-samples *t* test with Bonferroni correction ($\alpha = 0.05/15$).

^{a} $p < .001$ for each of the six measures according to a repeated measures ANOVA.

^{b} This column shows for how many of the 24 situations the mean score in the longer video is greater than the mean score in the shorter video. This comparison was made for the participants of group A versus the participants of group B. The videos of groups A and B had identical endpoints of the cars.

between 7 s and 20 s videos. Similarly, for the total distance error, there was no significant difference between 12 s and 20 s videos.

The total speed error shows a qualitatively different pattern than the total distance error, with no apparent saturation as a function of increasing video length (Figure 8). A statistically significant improvement is observed even from 12 s videos to 20 s videos. Moreover, the effects of video length are robust: in the group A versus group B comparison, 23 out of 24 videos with the same endpoint showed a better score for the longer video (Table 2).

The geometric difference score shows a weaker overall effect size (η^2) than the other measures, which may be because these scores exhibit strong situation-specific effects, with some situations yielding a notably better score than others (Figure 9). Nonetheless, the A versus B comparisons are consistent in the sense that longer-lasting videos yielded a lower difference score in 20 out of 24 situations. There was also no statistically significant difference anymore between 7 s and 20 s videos (Table 2).

3.3.3 Eye tracking

The distribution across the four areas of interest (i.e., a measure of attention distribution) and the glance frequency to the mirrors (i.e., a measure of gaze activity) as a function of observation time are shown in Figure 10. It can be seen that at the beginning (2–4 s),

participants distributed their attention approximately equally between the front view and the mirrors. Near the end (7–20 s), however, participants were more likely to glance at the road than at the mirrors. Furthermore, in agreement with Over et al. (2007) and Unema et al. (2005), we found a decrease in glance frequency with increasing observation time.

3.3.4. Correlation between video length and dependent measures, partialling out objective scenario difficulty

For all dependent measures, differences occurred between situations, even when the video length and traffic density were the same (Figures 4–9). Several characteristics of surrounding traffic might influence task performance. In particular, participants underestimated the distance to objects, and had more difficulty in estimating the position and speed of a car that is further away.

For this reason, we calculated an objective index of difficulty of the video, by summing the distances between the endpoints of 4/6 cars and the ego-vehicle. Table 3 shows the Spearman rank-order correlations between the mean score on the dependent measure per situation and the objective difficulty of the situation ($N = 24$). It can be seen that objective difficulty accounts for some of the situation-specific effects, in particular for the total distance error and total speed error. Furthermore, Table 3 shows the correlations between the dependent measures and video length. It can be seen that the strongest effect was observed for self-reported time sufficiency, whereas the weakest effect occurred for the geometric similarity, essentially mirroring the findings in Table 2. The third column of Table 3 shows again the correlations between the dependent measures and video length, but now after partialling out the objective difficulty. It can be seen that the partial correlations are slightly stronger than the zero-order correlations, in particular for the total distance error and total speed error. These findings indicate that when removing the effect of objective situation difficulty, the effects of video length becomes even stronger.

3.3.5. Effect of personal characteristics and driving experience

Previous research showed that in situations of transitions of control, experienced drivers are quicker to achieve SA than novice drivers (Wright et al., 2016). It has also been found that experienced drivers perform better than novices when asked to estimate the number of cars around them (Baumann et al., 2008).

Table 3. Spearman correlations between dependent measures, and measures of objective situation difficulty and video length ($N = 24$ situations).

Measure	ρ with objective difficulty (group A / group B)	ρ with video length (group A / group B)	Partial ρ with video length (group A / group B)
Time sufficiency (%)	-0.10 / -0.05	0.91 / 0.93	0.90 / 0.93
Difficulty (%)	0.42 / 0.43	-0.66 / -0.40	-0.70 / -0.49
Error in the number of placed cars (#)	0.20 / 0.52	-0.51 / -0.52	-0.49 / -0.62
Total distance error (m)	0.67 / 0.78	-0.35 / -0.23	-0.46 / -0.69
Total speed error (–)	0.52 / 0.31	-0.51 / -0.57	-0.68 / -0.73
Geometric difference (–)	0.35 / 0.28	-0.25 / -0.39	-0.32 / -0.45

We performed a correlational analysis to explore whether driving experience relates to performance at the SA task. Table 4 shows that participants who drive more frequently had a statistically significantly lower total distance and speed error. It is further interesting to observe that the subjective measures (time sufficiency and difficulty) exhibited a statistically significant correlation with each other, but did not correlate significantly with any of the objective measures. This indicates that participants who thought they did not have enough time or reported that the task was difficult did not necessarily perform poorly at the reproduction task. Finally, the eye-scanning measures were not significantly correlated with the performance measures.

3.4. Discussion and Conclusion

The aim of this research was to assess the effect of viewing time on SA operationalized as reproduction performance of a traffic situation. We applied three complementary types of statistical analyses: (1) a main effect of video length, (2) a between-subjects comparison of participants; the videos for these two groups were identical except that one of the two videos started earlier than the other, and (3) a correlation between video length and task performance while removing the effect of objective situation difficulty. The first analysis is useful for gauging the overall effect of video length, whereas the latter two methods account for situation-specific variance that may exist and thus serve as a confirmation.

The self-report measures confirmed that participants found the task more demanding if less time was available. This manipulation check validates our experiment and shows that the amount of time was manipulated in a range for which participants experience strong and consistent effects in time and difficulty.

Table 4. Spearman rank-order correlation matrix among personal characteristics and dependent measures).

	1	2	3	4	5	6	7	8	9	10	11	12	13
1. Age (years)													
2. Gender (0 = female, 1 = male)	-.03												
3. License age (years)	.26	.11											
4. Licensure (years)	**.56**	-.15	**-.48**										
5. Driving Frequency (0 = Every day, 5 = never)	.26	-.23	-.12	**.38**									
6.Yearly mileage (0 = 0 km, 10 = more than 100,000 km)	-.06	.09	.28	-.29	**-.57**								
7. Time sufficiency (%)	.08	.14	.30	-.08	.20	-.06							
8. Difficulty (%)	-.22	-.32	-.24	-.14	.09	.00	**-.55**						
9. Error in the number of placed cars (#)	.29	-.25	.21	.07	.32	.03	-.07	.13					
10. Total distance error (m)	.08	-.32	-.13	.11	**.41**	-.03	-.14	.21	**.57**				
11. Total speed error (–)	.30	-.21	-.20	.33	**.35**	**-.35**	-.21	.10	.25	.32			
12. Geometric difference (–)	.06	-.16	-.07	.21	.34	-.09	.19	-.14	-.01	**.35**	**.37**		
13. Mean mirror glance frequency (Hz)	-.24	-.40	-.05	.09	.23	-.14	-.13	-.05	.13	.25	.10	.17	
14. Road centre gaze proportion (0–1)	.26	.40	.08	-.03	-.01	-.18	.23	-.21	-.16	-.31	.09	-.22	**-.79**

Note. Correlations that are significantly ($p < .05$) different from 0 are indicated in boldface. $N = 34$ for measures 1–6, $N = 30$ for measure 7, $N = 31$ for measure 8, $N = 32$ for measures 9–12, $N = 21$ for measures 13 and 14.

Concerning the accuracy of the number of cars and the positions of the placed cars, the largest effects of video length were obtained up to 7 s and 12 s, respectively. A 7 s threshold is in line with previous driving simulator research on take-over requests, in which a lead time of 7 s was found to be sufficient for taking over control in a basic traffic scenario (e.g., Gold et al, 2013). Improvements in relative speed perception, on the other hand, were obtained up to 20 s. The apparent lack of saturation of the accuracy of the speed estimation can be explained by the fact that humans have to deduce speed from *changes* in a scene. In other words, people first need time to scan the environment to establish where the cars are, and only then can they use their time for tracking these cars. This pattern was also reflected in the eye-tracking data, showing a decrease of glance frequency with viewing time. Future research may explore this aspect further; for example, in our study the video lengths were as randomized order; if participants know how much time they have on beforehand, they may exhibit a different viewing behaviour (Huebner & Gegenfurtner, 2010).

Additionally, we applied a measure of geometric difference between the placed and actual cars. This method establishes the accuracy of placed cars in relative terms and may be particularly suited for assessing whether participants have perceived the overall layout of a situation. One possible weakness of the geometric difference method as well as the total

distance error may be that longitudinal distance dominates lateral distance, and so these methods are not particularly sensitive to mistakes whereby the participant placed a car in the wrong lane. Gugerty (1997) solved this issue by applying more weight to lateral errors than to longitudinal errors. The uniqueness of our approach as compared to Gugerty's is that it did not make use of any such weighting factors; therefore we expect that our non-parametric method can be applied to other spatial memory or SA studies without adjustment. A follow-up analysis showed a statistically significant difference between 1 s and 3 s videos regarding the total lateral distance error, but no further improvements for 3 s videos and beyond. The lack of statistically significant effects beyond 3 s can be explained by the fact that once a participant has identified a car, he/she can easily remember whether this car was in the left, middle, or right lane, because these are only three discrete categories.

Endsley's model of SA includes (1) perception, (2) comprehension, and (3) projection as three ascending levels (Endsley, 2015). One may argue that our experiment focused predominantly on level 1 SA. Indeed, participants were asked to reproduce the situation without having to comprehend the relevance of the cars in the environment. In reality, certain cars may be more relevant than others when it comes to safety margins and controllability. For example, in real traffic, cars in the back may often be safely ignored, whereas cars in front could be on a collision course or bear direct consequence for future action. Moreover, participants in our experiment did not perform driving-related decisions or actions, which may normally be performed simultaneously with the assessment of the situation and therefore interact with the time required to obtain SA. For example, Gugerty (1997) found that if drivers were in control of the driving task (with keyboard arrows) they remembered hazardous car better as compared to when they were in passenger mode, whereas Mackenzie and Harris (2015) showed that participants were slower to detect hazards when driving themselves as opposed to passively viewing a video.

Even though our experiment emphasized level 1 SA, a unique aspect of our research is that it also measured an important facet of level 3 SA by means of the assessment of relative speed. In fact, by having knowledge of the distance and speeds of objects, it is possible to project how a situation will unfold. Recent research indicates that queries regarding level 3 SA awareness ('what happens next') may be particularly valid in the sense that they discriminate between inexperienced and experienced drivers (Jackson et al., 2009). These observations are in line with our results, which showed that participants who drove more frequently performed better at the distance and speed estimation tasks (Table 4). However,

our study was of a simple and highly controlled design in which cars did not change lanes or speed, and level 3 SA was probed indirectly; participants were not directly asked what would happen next. Follow-up research could assess such aspects of level 2 and 3 SA in greater depth, for example by including hazard precursors, which are defined as cues in the environment that place critical demands on the driver's understanding of an unfolding situation (Garay-Vega & Fisher, 2005; Underwood et al. 2011). Moreover, research could include lane changes, and vehicle acceleration and deceleration, such as cars which are braking for an emergency. It should be noted, however, that humans are unable to perceive acceleration directly but rather infer acceleration from changes in speed over time (Brouwer et al., 2002; Gottsdanker et al., 1961).

For all dependent measures, large differences were found between situations, even if these situations had the same video length (see Figures 4–9). Several characteristics of the traffic might influence task performance. As illustrated by the results in Table 3, interpreting the behaviour of a car that is further away becomes increasingly harder as distance increases. Moreover, we showed that the higher the traffic density, the harder it is to reproduce the traffic situation. These results indicate that it is not possible to give a general recommendation of the lead time that is required for issuing a take-over request; the required time strongly depends on the complexity of the traffic situation. This finding is in line with Gold, Körber, Lechner, and Bengler (2016) who showed that the higher the traffic density, the longer the take-over time, defined as the first measurable steering or braking response after receiving a take-over request. However, the difference between our study and most of the available empirical research on this topic is that we obtained systematic insight into the cognitive aspects of building up SA as a function of time, whereas the available research adopts a behaviourist approach by quantifying reaction times and steering/braking responses (e.g., Gold et al., 2013; see De Winter et al., 2014, for a review).

Several limitations have to be taken into account when interpreting the results. First, the traffic situations were relatively simple and did not involve features such as lane changes, curves, or decelerating vehicles. Second, the monitor provided a small field of view and low immersion. The experiment did not allow for head movement, and certain monocular and binocular depth cues were lacking in the computer animations. These hardware features may affect both task performance and eye activity. Third, this study was conducted with participants at an engineering university. Engineering students are not representative of the general population and are known to have above-average spatial skills (Wai et al., 2009). It

has been previously shown that older drivers showed similar take-over times as younger drivers (Körber et al., 2016), despite the fact that biological age has a strong negative correlation with memory and spatial task performance (Salthouse, 2009). Possibly, having many years of driving experience may protect against age-related cognitive decline. The topic of individual differences in SA awareness is a promising topic for further research (Gugerty & Tirre, 2000). Fourth, in our experiment participants were not sitting in an actual automated car, and no drowsiness or secondary tasks were induced, which are conditions that may have important effects on how quickly drivers gain SA, and how effectively they take-over control (Borowsky & Oron-Gilad, 2016; Feldhütter et al., 2016; Gibson et al., 2016; Neubauer et al., 2014; Schmidt et al., 2016; Schömig et al., 2015; Zeeb et al., 2016). Despite the obvious differences between an automated driving task and the present experiment, it should be noted that the tasks are similar: In automated driving, the driver may also be prompted to monitor the traffic situation (without necessarily touching the steering wheel) to regain SA. Fifth, inherent to SAGAT-type methods, participants might have started to forget the driving situation when completing the reproduction task. For example, an analysis by Gugerty (1998) showed that participants tended to forget the location of cars during the time it took them to report the locations of the cars. One improvement would be to replace the slider bars with a less time-consuming interface where participants can drag the cars directly with the use of a mouse or by touch.

In conclusion, this research showed that participants need a few seconds in order to estimate the basic topology of a situation, but substantial improvements in speed estimation were still achieved between 12 and 20 s videos. These findings may have important consequences for the development of automated cars, in particular automated driving systems for which evidence starts to grow that humans are not well adapted to a task where they have to be able to regain control in a limited time frame (Casner et al., 2016; Norman, 2015; Poulin et al., 2015; U.S. Senate Committee on Commerce, Science, & Transportation, 2016). Future research could use the method applied in this study in an interactive driving simulator or head-mounted display with an integrated eye-tracker.

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CHAPTER 4

TAKE OVER! A VIDEO-CLIP STUDY MEASURING ATTENTION, SITUATION AWARENESS, AND DECISION-MAKING IN THE FACE OF AN IMPENDING HAZARD

Abstract

In highly automated driving, drivers occasionally need to take over control of the car due to the limitations of the automated driving system. Research has shown that visually distracted drivers need about 7 s to regain situation awareness (SA). However, it is unknown whether the presence of a hazard affects SA. In the present experiment, 32 participants watched animated video clips from a driver's perspective while their eyes were recorded using eye-tracking equipment. The videos had lengths between 1 and 20 s and contained either no hazard or an impending crash in the form of a stationary car, in the ego lane. After each video, participants had to (1) decide (no need to take over, evade left, evade right, brake only), (2) rate the danger of the situation, (3) rebuild the situation from a top-down perspective, and (4) rate the difficulty of the rebuilding task. The results showed that the hazard situations were experienced as more dangerous than the non-hazard situations, as inferred from self-reported danger and pupil diameter. However, there were no major differences in SA: hazard and non-hazard situations yielded equivalent speed and distance errors in the rebuilding task and equivalent self-reported difficulty scores. An exception occurred for the shortest time budget (1 second) videos, where participants showed impaired SA in the hazard condition, presumably because the threat inhibited participants from looking into the rear-view mirror. Correlations between measures of SA and decision-making accuracy were low to moderate. It is concluded that hazards do not substantially affect the global awareness of the traffic situation, except for short time budgets.

4.1 *Introduction*

Highly automated driving systems permit the driver to engage in non-driving tasks but cannot drive automatically in all possible road environments and traffic situations. An important question, there, is how well human drivers are able to reclaim control from the automated car, and how much time is needed for a safe transition. In a recent meta-analysis of 129 experimental studies, Zhang, De Winter, Varotto, Happee, and Martens (2019) examined the determinants of take-over time, that is, how quickly after a take-over request the driver grabs the steering wheel or presses the brakes. This meta-analysis showed that take-over times depend on, among others, the urgency of the situation and the type of take-over request.

What is less studied, however, is take-over quality, that is, whether the driver makes a safe decision, which can be operationalized using indexes such as time to collision and crash occurrence (Radlmayr, Gold, Lorenz, Farid, & Bengler, 2014; Gold, Happee, & Bengler, 2018). An important prerequisite for a high-quality take-over decision is situation awareness (SA), which can be defined as 'knowing what is going on so you can figure out what to do' (cf. Adam, 1993). Several simulator studies have found that, in urgent conditions, drivers show mean take-over times of about 1 s (e.g., Cohen-Lazry & Katzman, 2018; Politis, Brewster, & Pollick, 2017). Although it is possible for drivers to grab the steering wheel or depress the brakes 1 s after a take-over request, it is debatable whether such a short time interval is sufficient for becoming situationally aware. Zeeb, Buchner, and Schrauf (2016) found that drivers achieved motor readiness (i.e., eyes-on-road, hands-on-wheel) "almost reflexively", and that the cognitive processing of the traffic situation (i.e., system deactivation) and take-over quality (i.e., deviations from lane center) were impaired if the driver was performing a secondary task while the automation was active.

Samuel, Borowsky, Zilberstein, and Fisher (2016) examined driver SA in situations where the driver received a take-over request 4 s, 6 s, 8 s, or 12 s before the appearance of a hazard. Eye-tracking analyses showed that drivers were less likely to detect the hazard for 4 s time budgets times as compared to 8 and 12 s time budgets. Similar results were obtained by Vlakveld, Van Nes, De Bruin, Vissers, and Van der Kroft (2018). They found that drivers were more likely to detect hazards for 6-s time budgets as compared to 4-s time budgets. A mediating role of SA was suggested by a study of Köhn, Gottlieb, Schermann, & Krcmar (2019). These authors found that improved self-reported SA and faster take-over times with temporary interruptions of the non-driving task compared to without. Yang, Karakaya,

Dominioni, Kawabe, and Bengler (2018) found that their LED strip concept, which informed drivers about automation functionality and potential hazards, yielded improvements in gaze behavior and take-over quality. Lu, Coster, and De Winter (2017), using a method inspired by Gugerty (1997), had participants observe 1 s to 20 s video clips of traffic situations from the driver's perspective. After each clip, participants had to rebuild the traffic situation in a top-down view. Lu et al. (2017) concluded that drivers needed about 7 s to regain SA, defined as having knowledge about the number of cars and the locations of those cars; up to 20 s were needed for also being aware of the relative speeds of the cars on the road.

A limitation of the study by Lu et al. (2017) was that the situations in the video clips were not hazardous. Hence, there was no actual need for participants to achieve SA and reclaim control from the automated driving system. On the one hand, the presence of a hazard may give 'meaning' to the situation; participants may be better able to achieve SA if they have to act in a functional context. This ties into theories of perceptual chunking: Participants are known to be better able to process and memorize situations if they extract semantic patterns (Egan & Schwartz, 1979). Similarly, in the domain of chess, expert chess players are better able to recall actual game positions as compared to random game positions (Gobet & Simon, 1996). On the other hand, the presence of a hazard can be expected to diminish global SA, because the hazard (e.g., a car standing still on the ego-lane) attracts attention, as a consequence of which the driver may fail to perceive other vehicles on the road. This phenomenon is analogous to the 'weapon focus' effect (Loftus, Loftus, & Messo, 1987).

This study aimed to examine participants' SA levels in non-hazard and hazard situations. Furthermore, before asking drivers to rebuild the situation, we required them to make a decision (no need to take over, evade left, evade right, or brake). We used non-interactive videos to ensure that each person experienced exactly the same visual stimuli, combined with an eye-tracker to measure the extent to which the hazard on the ego-lane distracts from viewing surrounding cars.

4.2   Methods

4.2.1   Participants

Forty people participated in the experiment as part of a MSc-level course at the Delft University of Technology. Students could also perform alternative assignments. The use of students is common in automated driving research (De Winter et al., 2014). In a meta-analysis

of take-over experiments, Zhang et al. (2019) found that as much as 46% of 119 experiments in which age data were available featured a mean participant age equal to or below 30 years. Although students usually have a driving license, they tend not to drive on a daily basis because they favor public transport or cycling. For this reason, special attention must be paid to data quality control.

In our study, three participants who indicated not having a driving license were removed from the analysis. Furthermore, we decided to exclude three participants who did not adhere to the instructions (e.g., not following up instructions, confusing 'take over' for 'overtake', assuming that the ego-car might brake automatically), one participant who performed poorly (sometimes placing zero cars in front of the car), and one participant who disclosed that her driving experience amounted to a 10 min driving exam only. Accordingly, 32 participants were retained in the analysis. Eye-tracking data from 1 out of the 32 participants were discarded due to a calibration problem.

The participants were 29 males and 3 females, aged between 22 and 29 years ($M = 24.2$, $SD = 1.8$). Participants held a driving license for an average of 5.5 years ($SD = 2.3$). In the last 12 months, 3 participants drove every day, 5 participants drove 4–6 days per week, 10 participants drove 1–3 days per week, 6 participants drove less than once per month, but more than once per month, 3 participants drove less than once per month, and 5 participants did not drive in the past 12 months. About half of the participants were Dutch and the other half were international, mostly from India.

All participants provided written informed consent. The research was approved by the TU Delft Human Research Ethics Committee.

4.2.2 Apparatus

The videos were presented on a 24-inch monitor with a display area of 531×298 mm. An SR Research EyeLink 1000 Plus eye tracker was used to record monocular eye movements at 2000 Hz. The monitor was positioned 95 cm in front of the participant and 35 cm behind the eye-tracking camera and IR light source. The distance between the table surface and the lower edge of the display area was 20 cm. The horizontal and vertical viewing angles were approximately 31° and 18°, respectively. The room lights were turned on, and window blinders were put down when the experiment started. Driving videos with animated traffic were generated with Prescan 8.0.0 (PreScan, 2017). The videos were shown for 1, 3, 6, 9, 12,

or 20 s at a frame rate of 20 Hz. The videos had a resolution of 1920×1080 pixels. Rear-view, left, and right mirrors were integrated into the video (see Figure 1).

Figure 1. The driving environment

4.2.3   *Situations*

The videos showed a three-lane highway with the ego car always driving in the middle lane at 100 km/h. In the 1, 3, 6, 9, and 12 s videos, five surrounding cars were included. The 20-s videos contained six surrounding cars, to avoid the impression that all videos included the same number of cars. The three lanes each contained one or two surrounding cars. Two to four cars drove in front of the ego car. The farthest car was 50 to 80 m away from the ego car. The surrounding cars drove at one of three constant speeds: 80, 100, or 120 km/h. The three lanes could host cars of all three speeds (80, 100, 120 km/h). In this way, we aimed to eliminate the international participants' expectancies regarding country-specific speed regulations (e.g., the fast lane is the left lane in the Netherlands, and the fast lane is the right lane in India). Between 0 and 3 cars drove 80 km/h, between 1 and 3 cars drove 100 km/h, and between 1 and 3 cars drove 120 km/h. A 20 km/h speed difference with respect to the ego-car was regarded as representative of the speed variation one might encounter on real roads. None of the cars changed lanes. Car models and colors were randomly selected from 13 colors and 10 models.

Twelve videos, in which there was no need to take over, were created. These non-hazard situations had lengths of 1, 3, 6, 9, 12, and 20 s. Six situations were created, which were then left-right mirrored to generate six more non-hazard situations.

In addition to the non-hazard situations, we created 16 videos in which there was a need to take over and avoid a collision. These hazard situations had lengths of 1, 3, 6, and 9 s. The hazard was a car in front that decelerated at 5 m/s^2 from the start of the video. This car stood still during the last second of the video to ensure the same looming effects for each video. At the end of the video, the distance between the ego car and the hazardous car was 19–22 m. At a speed of the ego car of 100 km/h, this means that a collision was unavoidable by means of braking. Cars in the adjacent left or right lane were slowing down or speeding up. In this way, the cars in the left or right lane could block an avoidance maneuver. The correct emergency strategies were as follows:

- evade (lane change) to the *right* to avoid a collision with the front and left car,
- evade (lane change) to the *left* to avoid a collision with the front and right car. These situations were left-right mirrored with respect to the 'evade right' situations,
- evade (lane change) to the *left* or *right* to avoid a collision with the front car, or
- *braking* without steering to minimize the impact of an unavoidable collision with the front car, and avoid a side collision with the left and right car.

Additionally, five training videos were created. The training videos had a length of 1, 3, 6, 9, or 12 s, and contained four to six surrounding cars with no hazard.

4.2.4 Procedure

The participants read and signed an informed consent form and completed a brief questionnaire about age, gender, and driving experience. They adjusted the height of their chair and head support to find a comfortable seating position. Participants had their head in the head support during the entire experiment.

Participants received task instructions on both the consent form and the monitor. Participants were informed that they would be watching short driving videos (between 1 s and 20 s) from a driver's perspective and were asked to imagine that they were the driver of an automated car. It was stated that after each video, they had to indicate their control strategy to avoid a collision, to rate the danger of the situation, to rebuild the scene by placing cars based on what could be remembered from the last frame of the video, and to rate the difficulty of the

car-placement task. It was also mentioned that all cars would continue to drive without changing speed or lane.

First, a standard nine-point calibration procedure of the Eyelink eye tracker was performed. The experiment started with five training videos. Next, participants completed three sessions. In Sessions 1 and 2, participants received the situations shown in Table 1, in random order. Half of the participants (those with an odd participant number) completed Set 1 in Session 1 and Set 2 in Session 2, and the other half (those with an even participant number) completed Set 2 in Session 1 and Set 1 in Session 2.

Table 1. Situations presented in Sessions 1 and 2

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Set 1	N1	N3	N6	N9	N12	N20	R3	R9	L1	L6	B3	B9	LR1	LR6
Set 2	NM1	NM3	NM6	NM9	NM12	NM20	R1	R6	L3	L9	B1	B6	LR3	LR9

Note. N = No need to take over situations, R = Evade right situations, L = Evade left situations, LR = Evade left or right situations, B = Brake situations, M = Mirrored. The number refers to the video length in seconds.

After each video, participants completed four tasks in the following order:

1) Decide: participants had to select one of four response options for taking over control from the automated car. The options were 'Evade Left', 'Evade Right', 'Brake Only', and 'No Need to Take Over' (see Figure 2A). Participants had 5 s to respond.

2) Rate Danger: Participants rated the danger of the situation on a scale from Completely disagree (0) to Completely agree (10), see Figure 2B. Participants had 10 s to respond.

3) Rebuild Situation: Participants rebuilt the situation by placing cars around the ego car based on the last moment of the previous video, see Figure 2C. Participants could pick and place cars, having different indications of speed (faster than the ego car, equal speed as the ego car, slower than the ego car). In the training trials, participants were shown the correct answer after they had rebuilt the situation.

4) Rate Difficulty: Participants answered the statement 'The rebuilding task was difficult' on a scale from Completely disagree (0) to Completely agree (10), see Figure 2D. The participants had 10 s to answer this question.
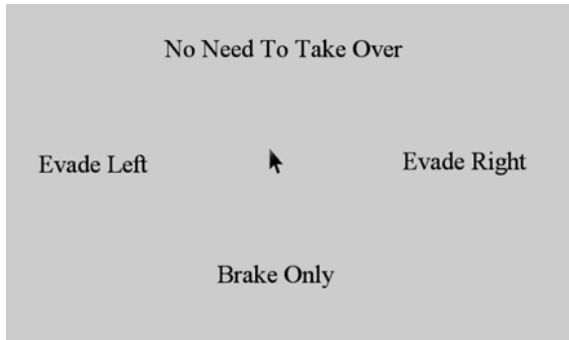
Figure 2A. Interface for making a decision in Sessions 1 and 2

Figure 2B. Interface for rating the danger of the situation
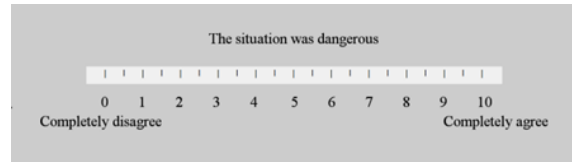

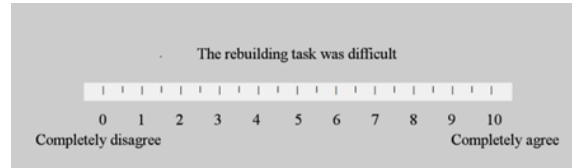**Figure 2C**. Interface for rebuilding the situation

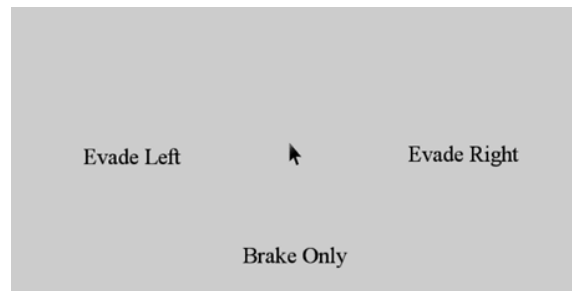**Figure 2D**. Interface for indicating the difficulty of the rebuilding task

Figure 2E. Decision-making interface in Session 3

Session 3 had the aim to examine whether the results obtained so far generalize towards more naturalistic conditions in which participants can decide to take over any moment they want and without having the need to rebuild the entire situation afterward. Participants were instructed on the monitor to again image that they were the driver of an automated car and to stop the video by pressing the spacebar as soon as they made a decision about how to take over control by evading left, evading right, or braking. Before Session 3, participants viewed the same videos as in Session 1, but in a new random order. First, participants completed three training trials. Next, the participants viewed 14 videos in which they stop the video by pressing the spacebar. If they pressed the spacebar, the interface of Figure 2E would appear. If they did not press the spacebar, they would finish watching the full video and Figure 2A would appear. Participants had 5 s to select a response using the interface. After this, participants rated the danger of the situation. There was no rebuilding task in Session 3.

In summary, each participant completed 50 trials: 5 training trials, 14 trials in Session 1, 14 trials in Session 2, 3 training trials before Session 3, and 14 trials in Session 3. The duration of the experiment per participant was approximately 60 minutes.

4.2.5   Dependent Measures

The following dependent measures were calculated for each trial.

- Decision accuracy (0 or 1). Whether the decision was correct (1) or incorrect (0).

- Decision time (s). How long participants took to select a decision using the interface. The maximum decision time was 5 s; if no decision was made, the result was coded as a missing value.

- Absolute error in the number of placed cars (#). The absolute error of the number of cars placed with respect to the true number of surrounding cars.

- Total distance error (%). The distance between the placed cars and true cars summed over all matched cars. The score was normalized so that a score of 0% corresponds to placing all cars precisely on top of the location of the true cars, and a score of 100% would correspond to a distance error equal to the sum of distances between the true cars and the ego car.

- Total speed error (-). The absolute speed error between the speeds of the placed cars and the speeds of the true cars, summed over all matched cars. A score of 0 would correspond to correctly indicating the speed of all placed cars; a score of 10 would correspond to reporting the incorrect speed of all 5 cars (slower where faster would be correct, and faster where slower would be correct).

- Self-reported difficulty (%). The subjective rating of the difficulty of the rebuilding task. The response on the scale from 0 to 10 was converted to a percentage.

- Self-reported danger (%). The subjective rating of the danger of the situation. The response on the scale from 0 to 10 was converted to a percentage.

- Take-over (0 or 1). Whether the participant pressed the spacebar (1) or not (0) while viewing the video (only in Session 3).

We matched the placed cars to the true cars using an algorithm by Lu et al. (2017). This algorithm finds a match by pairing all possible combinations of placed cars and true cars and selecting the combination with the minimal total distance error.

4.2.6 Analyses

We compared the mean scores on the dependent measures between the hazard and non-hazard situations. Paired-samples t-tests were performed between these two conditions, for 1 s, 3 s, 6 s, and 9 s videos separately. The 12 s and 20 s videos were not compared as there were no hazard situations having this length; the requirement of constant lead car deceleration (5 m/s2) prevented us from creating cars having realistic driving speeds. p-values smaller than .005 were deemed statistically significant (Benjamin et al., 2018). The within-subjects Cohen's *dz* was used as an effect size measure. At a sample size of 32 participants, an absolute *dz* value of 0.54 or higher is statistically significant, *p* < .005.

4.3   Results

4.3.1   Effect of hazard level (Sessions 1 & 2, passive viewing)

Participants' decisions were more accurate for non-hazard situations compared to hazard situations. In other words, participants were better at recognizing that there was no need to take-over than at indicating the correct take-over action (evade left, evade right, brake only) in case of a hazard. For 1-s videos, however, the difference between the two conditions was not statistically significant (Figure 3A).

An often-made error was pressing the brakes when there was no need to press the brakes, especially for short time budgets (Figure 3H). Pressing the brakes was the correct answer for 0% of the non-hazard situations and 25% of the hazard situations. Pressing the brakes may be a logical precautionary response for participants to minimize collision risk when being uncertain about the situation.

Participants' decision times for hazard and non-hazard situations were similar (Figure 3B). The exception was 1-s videos, where participants took significantly more time in non-hazard situations compared to hazard situations (Figure 3B).

Rebuilding performance improved with video length, which replicates the findings by Lu et al. (2017), see Figures 3C–3E. There were no statistically significant differences in rebuilding performance between hazard and non-hazard situations (Figures 3C–3E), except for the total distance error for 1-s videos, which was significantly higher for hazard than for non-hazard situations (Figure 3D). Additionally, participants found the rebuilding of hazard

and non-hazard situations equivalently difficult (Figure 3F). The hazard situations were perceived as much more dangerous than non-hazard situations (Figure 3G).

Appendix A provides the results of repeated-measures ANOVAs for testing the effect of time budget (i.e., video length) per dependent variable. The effects of time budget were roughly similar for hazard and non-hazard situations. The effect of time budget on total distance error was statistically significant for hazard situations, but not for non-hazard situations; this can be explained by the high distance errors for 1-s hazard situations. Effects of time budget on decision accuracy and decision time were significant for non-hazard situations but not for hazard situations, which can be explained by the poor decision accuracy for 1-s situations compared to 3-s, 9-s, and 12-s situations in the non-hazard condition (Figure 3A).
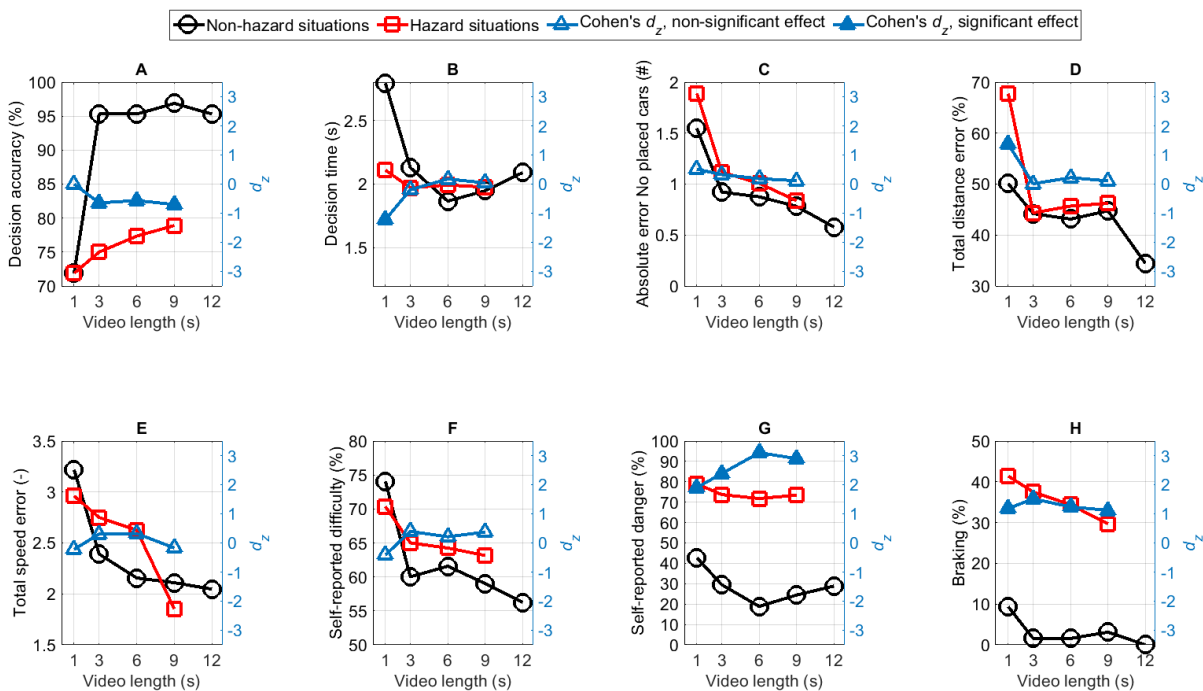
Figure 3. Results for Sessions 1 and 2 (passive viewing). Absolute dz values of 0.54 and higher are statistically significant, $p < .005$, and are marked as solid instead of open triangular markers. A positive dz means that the value is higher for hazard situations than for non-hazard situations.

4.3.2 Pupil diameter (Sessions 1 & 2, passive viewing)

We performed an additional analysis to examine whether the participants experienced the situations as emotionally arousing. Pupil diameter is an often-used index of emotional arousal (Bradley, Miccoli, Escrig, & Lang, 2008) and was used herein to compare hazard and non-hazard situations (Figure 4). The results for the mean pupil diameter near the end are

consistent with the notion that the approaching object induces emotional arousal. That is, the pupil dilated, especially for hazard situations.
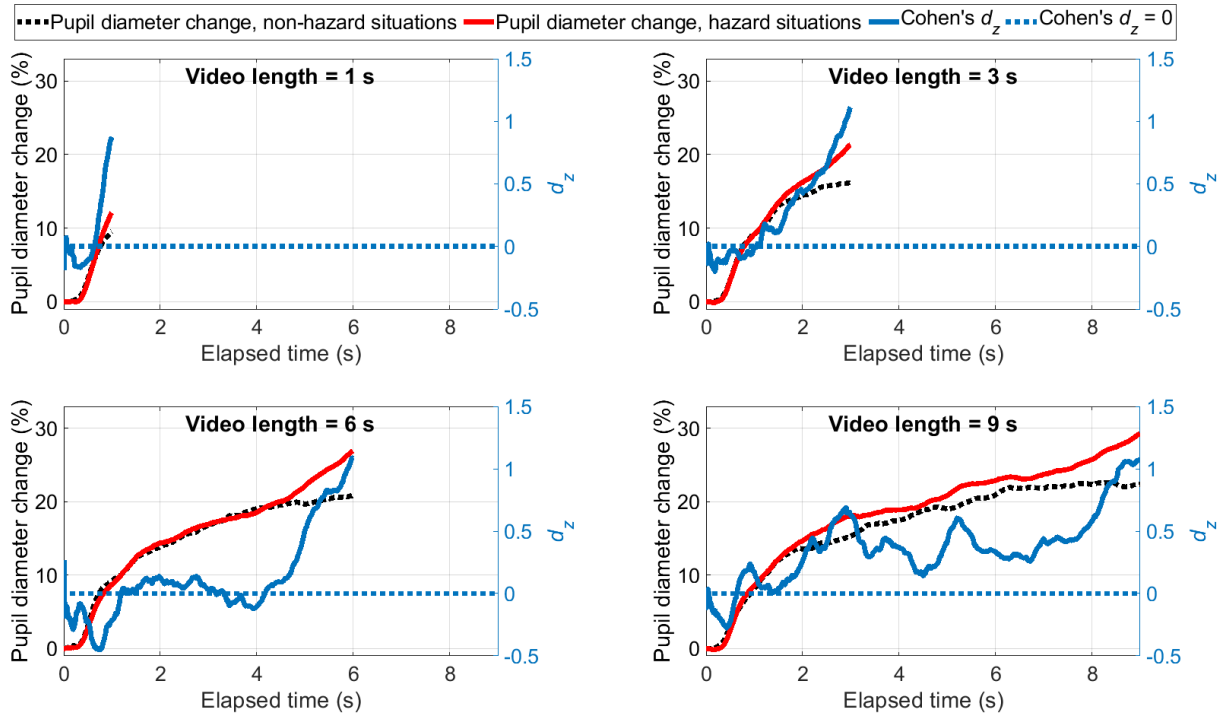
Figure 4. Pupil diameter change for the 1, 3, 6, and 9-s videos with respect to the pupil diameter at an elapsed time of 0 s. A positive dz means that the value is higher for hazard situations than for non-hazard situations.
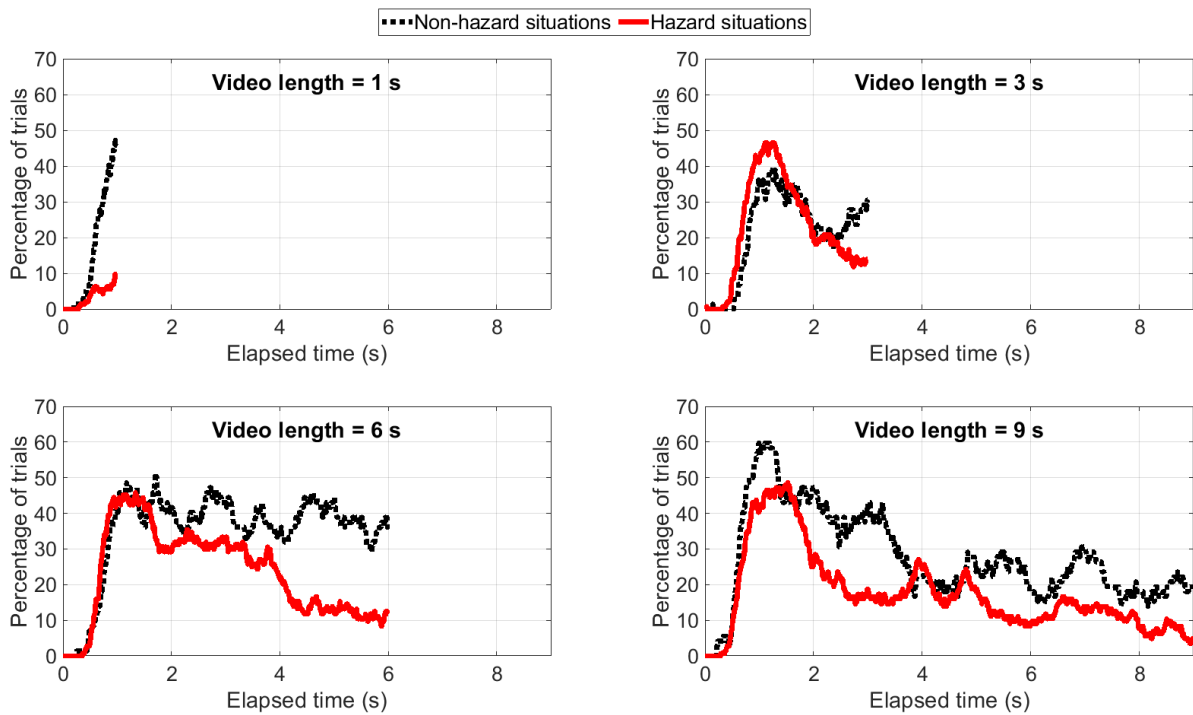
Figure 5. Percentage of trials in which the participant looks into the rear-view mirror for 1, 3, 6, and 9-s videos.

4.3.3 Attention distribution (Sessions 1 & 2, passive viewing)

One of our hypotheses was that the hazardous car attracts attention away from other cars. We examined participants' attention distribution towards the rear-view mirror. The findings are consistent with the weapon focus effect, especially for 1-s videos. At the end of 1-s hazard videos, only 10% of the participants looked into the rear-view mirror, compared to 48% for non-hazard videos (Figure 5).

4.3.4 Predicting decision accuracy (Sessions 1 & 2, passive viewing)

SA is regarded as a precursor of decision-making (Endsley, 1988). We examined Spearman rank-order correlations between decision accuracy and SA (Table 2). Participants with better decision accuracy (variable 3) did not have better SA regarding the number of placed cars (variable 5) and the total distance error (variable 6). However, there was a substantial correlation between decision accuracy and total speed error ($\rho = -0.43$).

Table 2. Spearman rank-order correlations matrix between personal characteristics and dependent measures ($N = 32$) for Sessions 1 and 2 combined

	Mean (SD)	1	2	3	4	5	6	7	8	9
1. Years of licensure	5.47 (2.29)									
2. Driving frequency (1 = never, 6 = every day)	3.50 (1.52)	0.38								
3. Decision accuracy (%)	82.14 (9.77)	-0.07	0.22							
4. Decision time (s)	2.06 (0.43)	0.07	-0.08	-0.34						
5. Absolute error in the number of placed cars (#)	1.10 (0.41)	0.10	-0.14	0.01	**0.47**					
6. Total distance error (%)	47.31 (9.31)	0.04	-0.31	-0.07	0.34	**0.75***				
7. Total speed error (-)	2.49 (0.61)	0.06	**-0.40**	**-0.43**	0.37	**0.58***	**0.54***			
8. Self-reported difficulty (%)	63.59 (15.45)	0.05	0.19	-0.19	0.16	0.04	-0.10	0.07		
9. Self-reported danger (%)	54.28 (10.75)	0.02	-0.08	-0.25	0.02	-0.12	-0.20	0.05	**0.43**	
10. Braking (%)	21.65 (10.22)	0.01	-0.19	**-0.62***	0.28	0.19	0.32	**0.39**	0.14	0.23

Note. Correlations that are significantly different from zero are marked in boldface for $p < .05$ and with an asterisk for $p < .005$. The scores for variables 3–10 were based on the average of 28 situations per participant.

The correlation matrix also showed that participants who drove more frequently (variable 2) had somewhat higher decision accuracy (variable 3) and better SA scores (variables 5–7). These correlations are consistent with Lu et al. (2017), but mostly too small to be statistically significant.

It can be argued that the correlations between decision accuracy and rebuilding task performance are weak because the rebuilding task measures global SA rather than local SA for making a correct decision. For example, cars far ahead of the ego car may be regarded as irrelevant for deciding how to avoid a collision. Accordingly, we explored the predictive power of local SA for decision-making. We examined whether the participant placed a car in the left or right lane within an absolute longitudinal distance of 10 m from the ego car.

Table 3 shows all combinations of correct decisions and decisions made by the participants, and the percentage of cases where the participant placed a car in the left or right lane. It can be seen that decision accuracy was high. To illustrate, in the 'Evade left' scenario, participants correctly indicated 'Evade left' in 99 cases, while the incorrect answer 'Evade right' was selected 0 times. The imperfect accuracy in the 'Evade left' scenario was mostly because participants selected 'Brake' in 23 cases, which is a reasonable response because it reduces the impact of a collision.

Table 3 further shows that there was no straightforward association between decision accuracy and local SA. For example, for 'Evade right' situations, participants mostly made the correct decision (90 times 'Evade right' vs. 27 times 'Brake', 5 times 'No need to take over', and 4 times 'Evade left'). Furthermore, participants who selected the correct response 'Evade right' afterward often recalled that a car was blocking the left lane (91% of 90 cases), indicating high local SA. Still this means that 9% of participants did not report a car in the left lane (despite making the correct decision). If participants made a mistake in the 'Evade right' scenario, they still tended to correctly report that there was a car in the left lane (80%, 100%, and 74% for 'No need to take over', 'Evade left', and 'Brake' decisions, respectively). Similarly, for the 'Brake' scenarios, in which a car was present in the left and right lanes, participants often did not place a car in those lanes, regardless of whether they selected the collect decision 'Brake'. These findings indicate a disconnect between implicit SA (what people decide to do) and explicit SA (what people recall afterward).

4.3.5 *Effect of hazard level (Session 3, active responding, without rebuilding task)*

In Session 3, participants' decisions were generally more accurate for non-hazard situations compared to hazard situations (Figure 4A). However, these effects were not statistically significant and appeared to be smaller without rebuilding tasks (Figure 4A vs. Figure 3A).

Table 3. Overview of decision accuracy (correct decision vs. decision made by the participant) and measures of local situation awareness (whether the participant placed a car nearby in the left or right lane).

Correct decision in the situation	Decision made by the participant	#	Car placed nearby in the left lane (%)	Car placed nearby in the right lane (%)
No need to take over	*No need to take over*	348	70	69
	Evade left	10	40	70
	Evade right	8	75	38
	Brake	11	73	55
Evade left	No need to take over	3	67	100
	Evade left	99	42	87
	Evade right	0	–	–
	Brake	23	57	74
Evade right	No need to take over	5	80	80
	Evade left	4	100	25
	Evade right	90	91	49
	Brake	27	74	41
Evade left or right	No need to take over	4	50	25
	Evade left	33	58	70
	Evade right	59	63	56
	Brake	26	35	54
Brake	No need to take over	6	100	83
	Evade left	6	50	83
	Evade right	6	83	67
	Brake	107	88	77
Any	No decision provided	21		
	Total	**896**		

Note. Correct decisions are marked in Italics. The total number of situations equals 896 (32 participants x 28 videos).
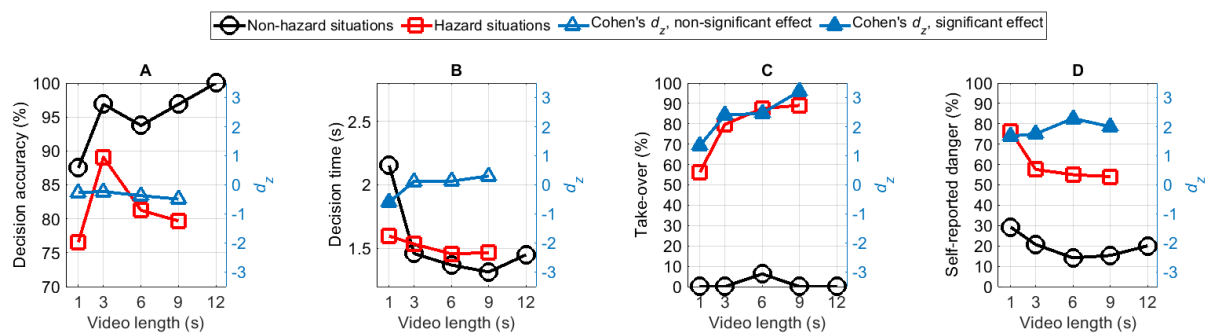
Figure 6. Results for Session 3 (active responding). Absolute *dz* values of 0.54 and higher are statistically significant, *p* < .005, and are marked as solid instead of open triangular markers. A positive *dz* means that the value is higher for hazard situations than for non-hazard situations.

Participants' decision time was faster in the active viewing conditions (Figure 6B) compared to the passive viewing conditions (Figure 3B), which could be a learning effect. The difference between the hazard situations and non-hazard situations followed the same pattern as in Sessions 1 & 2, with a faster decision time for hazard situations only for 1-s videos (Figure 6B).

Again, the hazard situations were found to be more dangerous than the non-hazard situations (Figure 6D). More specifically, participants found the hazard situations moderately dangerous (50% to 60% for 3–9 s videos, Figure 6D). In comparison, in Sessions 1 & 2, the situations were found to be highly dangerous (70% to 80% for 3–9 s videos, Figure 3G). The difference in self-reported danger between the with and without rebuilding task conditions could be because participants often took over (i.e., pressed the spacebar) before the video ended, especially when there was more time to do so (Figure 4C).

4.4   Discussion

This study compared participants' SA levels between hazard and non-hazard take-over situations for different time budgets. Our results replicate earlier research by showing that SA, operationalized as situation-rebuilding performance, improves with increasing time budget. We observed no major differences in SA between hazard and non-hazard situations, except for 1-s situations, where participants showed a larger total distance error in hazard situations compared to non-hazard situations (Figure 3D). The poor SA for 1-s hazard situations seems to be due to the weapon focus effect, where participants focused on the hazard while not looking at other cars such as cars in the rear-view mirror (Figure 6, left top).

For time budgets between 3 and 9 s, the decision accuracy was about 95% for non-hazard situations and only 75–80% for hazard situations. This difference can be explained because decision-making in hazard situations consists of two components: (1) recognizing that one has to take over (which may be easy because of the salient stationary car), and (2) selecting the right decision among three remaining options (Evade left, Evade Right, Brake only). Selecting the correct option among three options is likely more difficult than selecting 'No need to take over' in non-hazard situations. For the 1-s time budget, decision accuracy was poor for both non-hazard and hazard situations. An increase in time budget was not advantageous for reaching a correct decision in hazard situations, presumably because the nature of the hazards (i.e., cars in the left or right lane blocking a particular avoidance maneuver) became apparent at the end of the video.

Our rebuilding task resembles the popular Situation Awareness Global Assessment Technique, SAGAT (Endsley, 1988). The SAGAT has been criticized because it purportedly measures memory skills rather than SA (De Winter, Eisma, Cabrall, Hancock, & Stanton, 2019; Durso, Bleckley, & Dattel, 2006; Gugerty, 1998). Accordingly, it has been recommended that SA should not be measured using freeze-probe methods such as the SAGAT but by real-time probe or think-aloud methods instead (Jones & Endsley, 2004; Salmon, Stanton, & Young, 2012). Although this recommendation has merit, the advantage of our experimental method is that we separated the effect of stimulus presentation (i.e., showing the video) from the measurement of implicit (i.e., the decision-making task) and explicit SA (i.e., the rebuilding task). Already over 100 take-over studies are already available in the literature (Zhang et al., 2019). However, in each of these studies, participants took over by means of steering or braking, which means that the situation changes in person-specific ways. This in turn, inhibits a controlled assessment of how SA is affected by the presence of a hazard. This issue was corroborated in Session 3, where participants were allowed to take over when they felt this was needed. The findings confirmed that drivers adapt to the situation, in the sense that they anticipated the collision and moderated their task demands by preventing the hazard from coming close.

We used eye-tracking to measure participants' attention distribution while performing the task. The obtained results are consistent with, and a refinement of Lu et al. (2017), who used a relatively low-quality eye tracker that yielded relatively large amounts of missing data. The general pattern is that participants are initially likely to look into the rear-view mirror: around 1 s since the start of the video, participants looked into the rear-view mirror in about 50% of the cases. This value decreased with viewing time. These results can be interpreted as indicating that participants first try to obtain a general overview of the situation by locating where objects are, after which they allocate attention to how the situation unfolds in front of them. It is noted that in automated driving, drivers can relatively easily allocate their attention to other cars and the mirrors. In comparison, in manual driving drivers have to monitor the position of their car in the lane in order to steer their car (e.g., Navarro, Osiurak, Ovigue, & Reynaud, 2019).

Future research could attempt to measure SA in real-time using eye-tracking equipment (Moore & Gugerty, 2010). Having real-time knowledge of the driver's SA is attractive for creating automation systems that adapt to the driver's state. However, there are several caveats with such an approach. First, false positives and misses should be expected: a real-

time prediction of SA will not have perfect predictive validity for task performance (De Winter et al., 2019). Second, driving situations are dynamic, and surrounding cars subtend different viewing angles: Cars driving closely will absorb a large part of the driver's field of view, whereas cars driving far ahead will take up a small region. Our preliminary attempts to make a real-time index of SA stranded because our algorithms were unable to classify whether the participant was looking at the car in the left, right, or middle lane in case multiple cars drove far ahead of the ego car, despite the fact that we used an accurate eye tracker and a head support. Accordingly, it may be more fruitful to make a driver attention indicator by examining the driver's attention distribution based on how frequently the driver glances to large areas of interest, such as whether or not the driver looks at the road ahead (Cabrall et al., 2018).

We observed weak-to-moderate associations between global (Table 2) or local (Table 3) SA and decision accuracy. For global SA (i.e., error in the number of placed cars, distance error, speed error), the weak-to-moderate association can be explained because global SA is unneeded for avoiding a collision: cars far behind or far ahead are irrelevant at safety-critical moments. However, even for our measure of local SA, participants often made incongruent decisions. For example, some participants evaded to the left, even though they indicated there was a car in the left lane (Table 3). There are several explanations for this incongruence. In particular, participants had to decide under time pressure, which may have contributed to instinctive decision-making outside of conscious recall. Furthermore, participants may have acted based on previously learned habits such as to overtake via the left in accordance with traffic laws. This could explain why there were fewer mistakes in the 'Evade left' scenario as compared to the 'Evade right' scenario. A simulator study by Petermeijer, Bazilinskyy, Bengler, and De Winter (2017) concurs that drivers are likely to evade to the left in take-over situations. Furthermore, our SAGAT-type method, in which participants needed to position the cars in a top-down perspective, may have been difficult for participants because they had experienced the situation from an ego-centric perspective. In an early experiment using a similar method, Gugerty (1997) reported that "the direct and indirect measures were positively correlated (associated), suggesting that drivers' knowledge of nearby cars is largely explicit with little contribution of implicit knowledge." (p. 42). A closer inspection of Gugerty's results showed that correlations between explicit SA (rebuilding task performance) and implicit SA (hazard detection, blocking car detection, crash avoidance) were of only moderate strength (between -0.34 and -0.53, depending on whether all cars or only nearby

cars were included), despite aggregating over 80 trials per participant. Hence, our results are actually in line with those of Gugerty. In summary, an important take-home message is that knowledge of where other cars are (explicit SA) is not clearly related to what drivers do in a given emergency situation (implicit SA). Although explicit situation awareness (obtained via SAGAT methods) is a sensitive dependent variable in experimental studies (Endsley, 1988), it shows only moderate associations with task performance (for a survey see De Winter et al., 2019).

In addition to measuring eye-gaze direction, we used the eye tracker to measure pupil diameter. Our findings showed an elevated pupil diameter for hazard situations compared to non-hazard situations, near the end of the video. These observations are consistent with the notion that the impending hazard causes a stress response among subjects. It is noted, however, that pupil diameter is sensitive to light (e.g., bright and dark regions on the monitor). Hence, we cannot conclusively state that arousal is the sole cause of the results shown in Figure 6. Because of the sensitivity of pupil diameter to confounding variables such as the light reflex, we expect that pupillometry would not be fruitful for real-time applications in cars.

In summary, our experiment examined the effects on driver state of an impending hazard compared to no hazard. We showed that the effect of the hazard is large for the drivers' level of experienced danger ($dz = 2$ to 3 for self-reported danger, $dz = 1$ for pupil diameter) and small for SA ($|dz| < 0.5$). Thus, participants in hazard situations were able to achieve a level of SA that is comparable to non-hazard situations, except for 1-s time budgets where drivers have little time to look into the rear-view mirrors to assess the situation. We conclude that the answer 'How much time do drivers need to obtain SA?' is roughly independent of whether or not there is a hazard. Future research aimed at improving driving safety in take-over situations should be devoted to minimal risk solutions such as better automated emergency braking, evasive maneuvering systems, or lane change assistance so that drivers do not have to make time-critical decisions themselves or their bad decisions could be corrected. Future research could also aim to replicate our video-based experiment in a driving simulator with a 360-degree field of view, thus offering a higher degree of immersion. Such a method could also record driver input (steer, brake, accelerator position) instead of using discrete inputs using a computer mouse.

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Appendix A

We performed one-way repeated measures ANOVAs after rank-transformation (Conover & Iman, 1981), with the video length as the repeated-measures factor. Pairwise comparisons between video lengths were conducted by means of paired-samples *t*-tests. Effect sizes for the pairwise comparisons were expressed in terms of Cohen's d_z, a within-subjects effect size index (Faul et al., 2007). Results are shown in Table A1 (non-hazard situations) and Table A2 (hazard situations).

Table A1. Results of the repeated-measures ANOVA and effect sizes (d_z) of paired comparisons between video lengths (non-hazard situations of Sessions 1 and 2)

	df	F	P	η^2	1 vs. 3	1 vs. 6	1 vs. 9	3 vs. 6	3 vs. 9	6 vs. 9
Decision accuracy (%)	3,93	13.3	**< .001**	0.30	**-0.68**	**-0.78**	**-0.78**	-0.08	-0.08	-0.02
Decision time (s)	3,93	27.6	**< .001**	0.47	**1.00**	**1.39**	**1.20**	0.42	0.30	-0.15
Absolute error in the number of placed cars (#)	3,93	13.6	**< .001**	0.31	**0.86**	**0.80**	**1.06**	0.09	0.24	0.12
Total distance error (%)	3,93	3.5	.018	0.10	0.45	0.43	0.45	0.03	-0.03	-0.06
Total speed error (-)	3,93	10.1	**< .001**	0.25	**0.86**	**0.76**	**0.85**	0.16	0.24	0.03
Self-reported difficulty (%)	3,93	17.6	**< .001**	0.36	**0.96**	**0.79**	**1.06**	-0.15	0.09	0.22
Self-reported danger (%)	3,93	36.3	**< .001**	0.54	**0.74**	**1.57**	**1.13**	**0.96**	**0.58**	**-0.61**
Braking (%)	3,93	2.5	.061	0.08	0.35	0.35	0.25	0.00	-0.10	-0.18

Note. Significant effects ($p < .005$) are listed in boldface.

Table A2. Results of the repeated-measures ANOVA and effect sizes (d_z) of paired comparisons between video lengths (hazard situations of Sessions 1 and 2)

	Df	F	P	η^2	1 vs. 3	1 vs. 6	1 vs. 9	3 vs. 6	3 vs. 9	6 vs. 9
Decision accuracy (%)	3,93	1.52	.251	0.05	-0.18	-0.28	-0.36	-0.06	-0.18	-0.14
Decision time (s)	3,93	1.14	.337	0.04	0.23	0.27	0.28	0.02	0.08	0.07
Absolute error in the number of placed cars (#)	3,93	46.9	**< .001**	0.60	**1.28**	**1.52**	**1.75**	0.20	**0.67**	0.43
Total distance error (%)	3,93	42.1	**< .001**	0.58	**1.76**	**1.60**	**1.65**	-0.11	-0.11	-0.01
Total speed error (-)	3,93	10.6	**< .001**	0.25	0.15	0.29	**0.85**	0.17	**0.78**	**0.68**
Self-reported difficulty (%)	3,93	7.1	**< .001**	0.19	0.45	**0.65**	**0.69**	0.16	0.16	0.02
Self-reported danger (%)	3,93	6.5	**< .001**	0.17	0.45	**0.57**	0.51	0.20	0.06	-0.17
Braking (%)	3,93	2.9	.038	0.09	0.12	0.33	0.46	0.19	0.33	0.19

Note. Significant effects ($p < .005$) are listed in boldface.

CHAPTER **5**

**BEYOND MERE TAKE-OVER REQUESTS:
THE EFFECTS OF MONITORING
REQUESTS ON DRIVER ATTENTION, TAKE-
OVER PERFORMANCE, AND ACCEPTANCE**

Abstract

In conditionally automated driving, drivers do not have to monitor the road, whereas in partially automated driving, drivers have to monitor the road permanently. We evaluated a dynamic allocation of monitoring tasks to human and automation by providing a monitoring request (MR) before a possible take-over request (TOR), with the aim to better prepare drivers to take over safely and efficiently. In a simulator-based study, an MR+TOR condition was compared with a TOR-only condition using a within-subject design with 41 participants. In the MR+TOR condition, an MR was triggered 12 s before a zebra crossing, and a TOR was provided 7 s after the MR onset if pedestrians crossing the road were detected. In the TOR-only condition, a TOR was provided 5 s before the vehicle would collide with a pedestrian if the participant did not intervene. Participants were instructed to perform a self-paced visual-motor non-driving task during automated driving. Eye tracking results showed that participants in the MR+TOR condition responded to the MR by looking at the driving environment. They also exhibited better take-over performance, with a shorter response time to the TOR and a longer minimum time to collision as compared to the TOR-only condition. Subjective evaluations also showed advantages of the MR: participants reported lower workload, higher acceptance, and higher trust in the MR+TOR condition as compared to the TOR-only condition. Participants' reliance on automation was tested in a third drive (MR-only condition), where automation failed to provide a TOR after an MR. The MR-only condition resulted in later responses (and errors of omission) as compared to the MR+TOR condition. It is concluded that MRs have the potential to increase safety and acceptance of automated driving as compared to systems only providing TORs. Drivers' trust calibration and reliance on automation will need further investigation.

5.1 Introduction

5.1.1 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).

5.1.2 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, 2017). 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, 2018, for reviews). While time budgets between 5 and 7 s are often used (Zhang et al., 2018), 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 seconds of preparation time.

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".

5.1.3 *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 with their hands on the 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, and Bengler, 2013), the authors suggested that the MR concept is effective in terms of safety. Louw et al. (2017a, 2017b) 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 study 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 its colour or blinking patterns 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 et al., 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.

5.1.4   Reliance Effects

Tijerina et al. (2017) showed that a 'cry wolf' effect occurs if the uncertainty notification was issued frequently without an actual need for a response. Similarly, a study evaluating the effects of advisory warning systems in automated driving showed that false alarms caused a cry-wolf effect (Naujoks, Kiesel, and Neukum (2016). 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. In the present study, we examined whether drivers over-relied on the TOR, despite the fact that they were being forewarned by means of an MR.

5.1.5   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.

An additional aim of this study was to examine whether drivers' exhibited overreliance on the TORs. 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. To evaluate this risk, 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.

5.2   Methods

5.2.1   Participants

Forty-one participants (35 males, 6 females) were recruited through Facebook and University whiteboard advertisements. Their mean age was 29.6 years ($SD = 7.0$, ranging from 20 to 57 years). All participants had a valid driving license (which was 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.

5.2.2 *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-inch handheld tablet (iPad 2) was provided to the participants for performing a non-driving task. The vehicle and the cabin are shown in Figure 1.

Figure 1. The TU Munich Driving Simulator. Left: full-vehicle mock-up; Right: cabin.

5.2.3 *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 overreliance on the TOR signal. This condition was analysed separately.

The system MR+TOR system consisted of five automation states, with corresponding status icons shown on the dashboard (Figures 2 & 3). When the automation is unavailable, a white car on a light blue road is shown in the top centre (Figure 2a) and the driver needs to drive manually. When the requirements for automated driving are fulfilled, a verbal notification "Automation available" was issued, and a green steering wheel icon was shown (Figure 2b). The driver could press a button on the steering wheel to activate the automation (the icon then changed to Figure 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 verbal notification "Please monitor" following a gong sound, and a yellow eye-shaped icon (Figure 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 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 2e and Figure 3 (right) show the visual display for the TOR: an orange hands-on-the-wheel icon in the lower centre of the dashboard, and the automation state icon back to "automation unavailable" (Figure 2a). Upon receiving the TOR, the driver had to take over by steering and/or braking 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.

5.2.4   *Experimental design and test scenarios*

A within-subject design was used, meaning that each participant completed all three conditions (MR+TOR, TOR-only, MR-only) in three separate sessions. The MR+TOR and TOR-only conditions were counterbalanced, whereas the MR-only condition was always presented in the last (i.e., third) session.
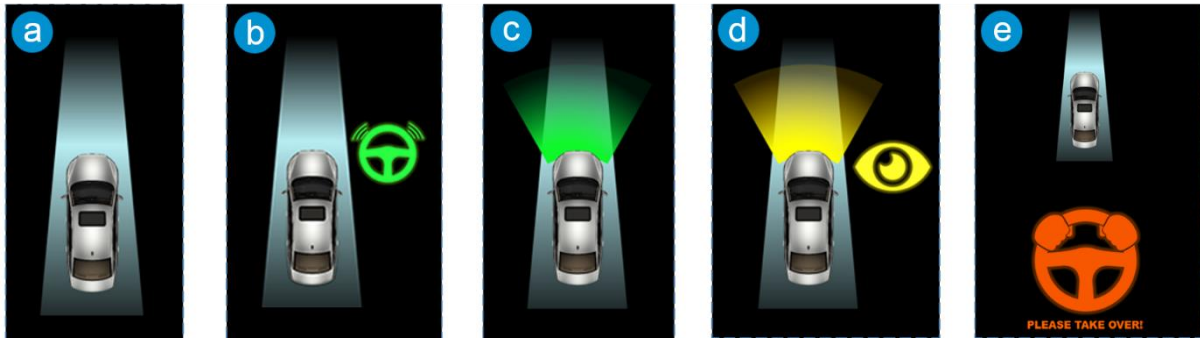
Figure 2. Screenshots of the visual interface for the five system states. a) automation unavailable; b) automation available but not yet activated; c) automation activated; d) monitoring request; e) take-over request.

Figure 3. Photos of the instrument cluster with automation status. Left: automation available, corresponding to Figure 2b; Right: take-over request, corresponding to Figure 2e.

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 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.

The TOR was provided at the moment the first pedestrian became visible on the edge of the side walk. The automation was deactivated together with the presentation of the TOR, which led to a slight deceleration of the vehicle if the drivers did not intervene. Based on pilot studies and the available literature, we opted for a time budget of 5 s; thus, the car would crash into the pedestrians in 5 s if the participant did not intervene. This time budget was expected to be mentally demanding, but should not result in a high number of collisions with the pedestrians (collisions would have been undesirable due to ethical reasons). A recent meta-analysis by Zhang et al. (2018) found that about 70% of the time budgets used in the experimental literature are between 5 and 7 s. From a study of Lu et al (2017), we reasoned that 7 s is sufficient for regaining situation awareness in a simple traffic scenario, whereas according to Gold, Damböck, Lorenz, and Bengler (2013), 5 s would be a challenging, yet manageable, time budget for visually distracted drivers to take back control.

In the MR+TOR condition, an MR was issued 12 s (166.67 m) before reaching the zebra crossing (i.e., the TOR was provided 7 s after the MR onset). The MR was deactivated when passing the zebra crossing without pedestrians (Figure 4 Right). In each of the two conditions, the sequence of the five zebra crossings was randomized. The duration of each session was approximately 14 min.

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 5 provides an illustration of the order of sessions and events for one participant.

5.2.5   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.

Figure 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 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).

5.2.6   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.

5.2.7 *Dependent variables*

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

5.2.7.1 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).

5.2.7.2 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.

5.2.7.3 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 the 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.

5.3   Results

5.3.1   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 1 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.

**Table 1**. 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

5.3.2   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 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).

From Figure 6, 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 for a figure with the mean speed).
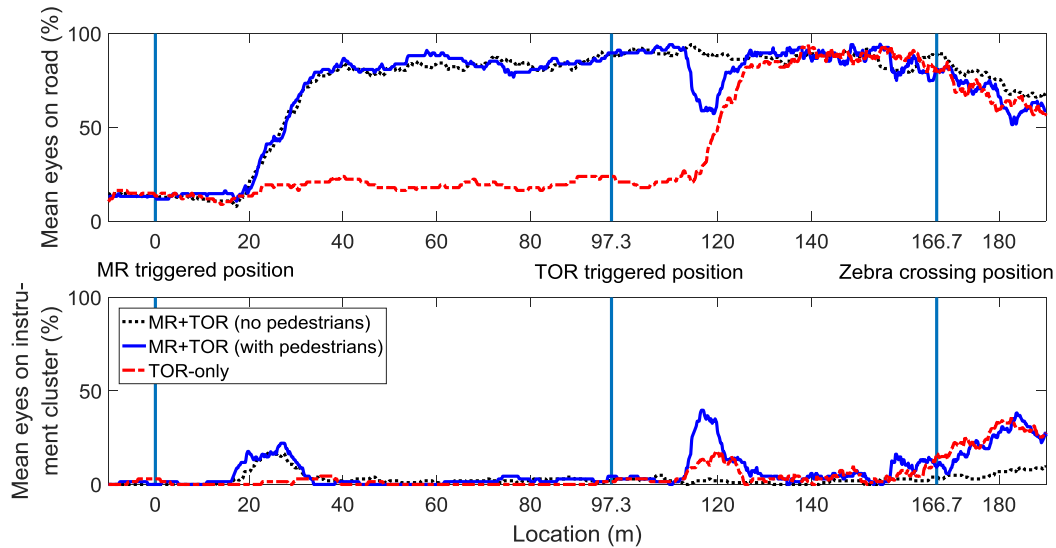
Figure 6. Participants' visual attention allocation on the windshield (upper plot) and instrument cluster (lower plot) for the MR+TOR and TOR-only conditions. Three vertical lines from left to right are the locations of the MR (0 m; time to zebra crossing = 12 s), TOR (97.3 m; time to zebra crossing = 5 s), and zebra crossing.

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 2 and Figure 8). 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 2 and Figure 9a). This finding indicates that participants were equivalently distracted in both conditions, as could be expected.

5.3.3   *Take-over performance*

Figure 7 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 2 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 and Table 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 8, 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 2, Figure 9b and Figure 9c).

5.3.4 Subjective evaluation

5.3.4.1 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 3).

5.3.4.2 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 ($M = 80.6$, $SD = 17.1$), $t(37) = 3.42$, $p = 0.002$, $r = 0.57$.

5.3.4.3 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 ($M = 96.1$, $SD = 5.8$), $t(37) = 1.25$, $p = 0.220$, $r = 0.64$.
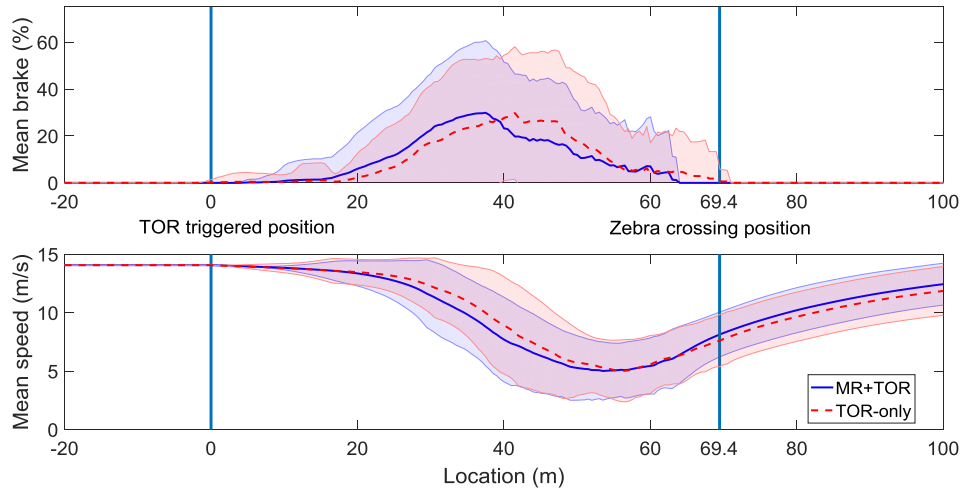
Figure 7. Means and standard deviations across events of the brake position and driving speed in the take-over scenarios in the MR+TOR and TOR-only conditions as a function of travelled distance. The vertical lines mark the start of the TOR (0 m) and the position of the zebra crossing (69.4 m). Note 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 2. 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/s²)	Minimum TTC (s)
MR+TOR	*M (SD)*	1.85 (0.51)	17.71 (13.98)	-0.38 (3.26)	1.86 (0.59)	7.91 (5.49)	-8.42 (0.97)	2.83 (0.54)
TOR-only	*M (SD)*	1.76 (0.73)	16.43 (14.05)	2.64 (1.88)	2.30 (0.61)	8.72 (4.32)	-8.72 (1.00)	2.56 (0.72)
Paired t-test	*t(37)*	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

Table 3. 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%).
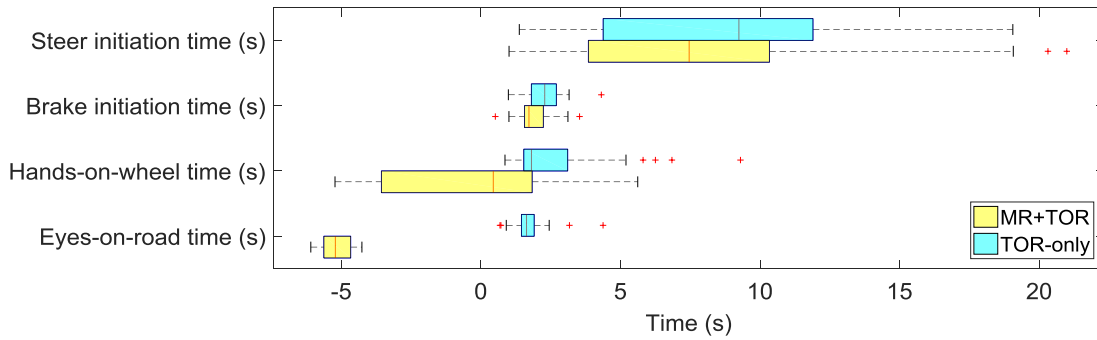
Figure 8. Box plots at the level of participants for eyes-on-road, hands-on-wheel, braking, and steering. The figure is created so that the temporal sequence of events is illustrated. The TOR is provided at 0 s, while the MR is provided at -7 s. The eyes-on-road time in the MR+TOR condition is the response 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.
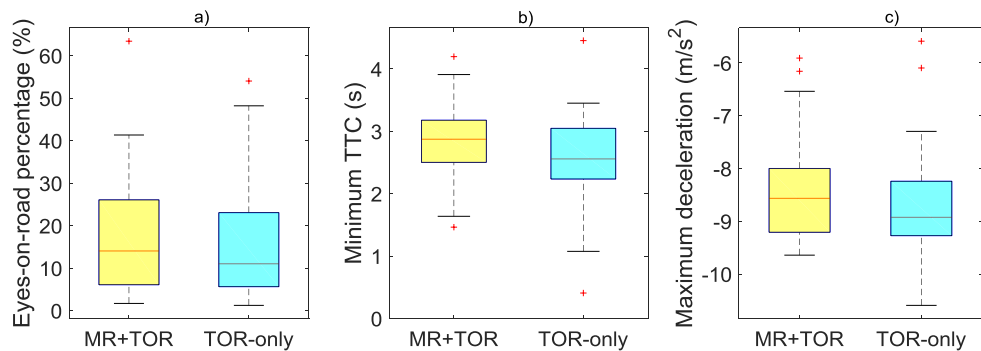
Figure 9. Boxplots at the level of participants for a) percentage time eyes-on-road, b) minimum TTC, and c) maximum deceleration. Three participants who crashed (i.e., minimum TTC = 0 s) were not included in this figure.

5.3.4.4 Trust

All trust-related scores for the MR+TOR and TOR-only conditions are shown in Table 4. 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.

5.3.5   *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.

Table 4. 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
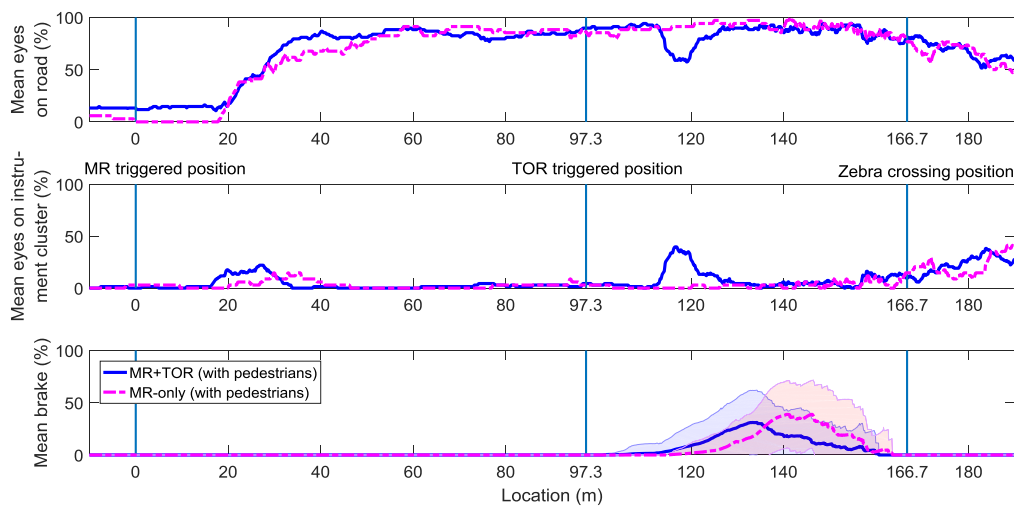
Figure 10. Participants' mean visual attention allocation across events on the windshield (upper plot) and instrument cluster (middle plot) and means and standard deviations across events of the brake position (lower plot) in the pedestrians crossing scenarios in the MR+TOR and MR-only conditions as 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).

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 expectations of, 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 10. 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.

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 5). 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 5 and Table 6, 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 5. Means and standard deviations of participants for the braking measures in the MR+TOR and MR-only conditions

	Maximum deceleration (m/s^2)	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 6. 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/s^2)				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**

5.4   Discussion

5.4.1   Main findings

The main aim of this study was to investigate whether drivers are responsive to MRs by redirecting their attention to the road, whether drivers unnecessarily take over control when no action is needed, and whether drivers have a shorter take-over 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 seconds 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/s^2, 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 unneeded 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 (Gold et al., 2013; Cohen-Lazry et al., 2017; Dziennus et al., 2016; Yang et al., 2017; Helldin et al., 2013), 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.

5.4.2 Reliance on the TOR

An additional aim of this study was to examine whether people over-rely on the TOR, despite the fact that they have received an MR prompting them to monitor the driving environment. Previous research suggests that notifications with a low probability of requiring an actual intervention may cause under-reliance (Tijerina et al., 2017), a phenomenon also known as the cry-wolf effect (Bliss, 1993; Breznitz, 1983; Dixon, Wickens, & McCarley, 2007; Wickens, Dixon, Goh, & Hammer, 2005; Zabyshny & Ragland, 2003). The opposite effect was observed in the final trial of our experiment: When drivers who were previously exposed to perfectly reliable TORs were provided with only an MR, they showed worse take-over 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, despite the fact that they were looking at the driving environment and were told that the TOR would be available only if the critical event were detected successfully. This overreliance 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 overreliance 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.

5.4.3   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 seconds before the collision) and taking over (i.e., 5 seconds 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, the MRs were tested in a rather short experiment. It is possible that non-compliance to the MRs becomes apparent if drivers were to use the system for a longer time on real roads. Finally, simulator fidelity may be an issue. The absence of physical motion cues may have an effect on how drivers brake (Boer et al., 2000; Siegler et al., 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.

5.5   Conclusion

In summary, the observed effects of MRs are promising: the MRs directed the drivers' attention to the road without the necessity for them to take over control of the vehicle, improve the 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. Finally, we caution that the provision of MRs does not guarantee that no collisions will occur. We 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 even though their eyes were on the road. Future research should be conducted on the topic of overreliance on take-over requests and individual differences in the use of automated vehicles.

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CHAPTER 6

CONCLUSION AND DISCUSSION

6.1 Conclusion

Using a theoretical analysis and three empirical studies, this dissertation explored driver behaviour during transitions in automated driving. Drivers were exposed to simulated control transition scenarios in simulators with different levels of fidelity (i.e., desktop computer vs. immersive driving simulator). The results, which included both subjective and objective evaluations, provide an understanding of how drivers process information and respond to the take-over scenarios.

Chapter 2 created a theoretical structure and a systematic view of transitions of control in automated driving. Chapter 3 investigated the situation-awareness rebuilding process as a function of time budget in non-hazard traffic in a PC-based experiment. Chapter 4 studied drivers' performance and decision-making in hazardous situations with different time budgets. Finally, Chapter 5 examined an alternative way of interaction by giving a preparatory monitoring request in take-over scenarios with a short time budget.

1) A 'transition' in automated driving was defined based on the definition of driving states, where driving states were derived from primary driving task allocations. The transitions were classified into control transitions and monitoring transitions. Control transitions were categorized into four types.

2) Participants need about 7 s for estimating the positions of the surrounding vehicles, but speed estimation keeps improving from 12 s to 20 s in non-hazard traffic scenarios.

3) The effect of the presence of a hazard in the ego-lane, in comparison to a non-hazard situation, is large when it comes to drivers' subjective level of experienced danger and small for situation awareness. Participants in hazard situations are able to achieve a level of situation awareness that is comparable to non-hazard situations, except for extremely short time budgets of 1 s.

4) Monitoring requests direct the drivers' attention to the road without the need to physically control the vehicle. The provision of a monitoring request improves the response times to a subsequent take-over request. The monitoring-request & take-over-request design was evaluated positively regarding subjectively workload, usefulness, and satisfaction.

6.2   Discussion

This section follows the order of the main conclusions drawn from the thesis. I analyse and discuss the aims and the methods that led to the conclusions. Also, the limitations and recommendations of the studies are discussed.

Chapter 2 built a theoretical framework for a better understanding of transitions from human factors point of view in automated driving. The definition of driver states differs from the SAE (SAE, 2016) and BASt (Gasser, & Westhoff, 2012) levels of automated driving. This framework intends to describe what the driver and the automation are doing at a particular moment instead of what they should be doing do as in the 'levels of automated driving'. The classification of control transitions (AIAC, AIDC, DIDC, DIAC) intends to cover all scenarios involving discrete control authority reallocations. Based on the analysis, we distinguish between active transitions (DIDC and AIAC) and passive transitions (DIAC and AIDC transitions). The lack of preparations in passive transitions could lead to safety hazards, which prompted a further investigation of the cognitive processes during AIDC transitions in Chapters 3 and 4. The distinction between monitoring transitions and control transitions is required for understanding transitions between 'being out-of-the-loop' and 'being in-the-loop'. We believe that monitoring and control transitions will become common if Level 3 automation becomes widely available. In Chapter 5, we offer an innovative design: the use of monitoring requests. Note that we did not include an adaptive control allocation in the classification: a system that adapts to the human could be beneficial for effective human-machine interaction (Hancock et al., 2013; Kaber & Endsley, 2004; Parasuraman et al., 1996).

AIDC transitions, also known as take-overs, have been the focus of ample human factor research in the automated driving domain. However, there are still many gaps in other types of control transitions even though they may not pose an obvious safety risk. DIDC transitions are actually occurring in most of the current Level 2 systems, where the driver is required to monitor the environment constantly. Victor et al., (2018) argued that people may not be able to react to hazards even seeing them. Various accidents have happened due to the latency of the driver's response, despite the fact that the driver was performing the monitoring task. It can be expected that the prevalence of DIDC transitions will reduce in the future due to ongoing technological improvements. However, more research is needed to examine whether current human-automation interaction designs that aim to keep the driver in the loop (see e.g., Cabrall et al., 2019) are adequate, so that if a DIDC happens, it will still be safe. In some

other cases, if a driver's inability or impairment is detected by the driver monitoring systems, AIAC transitions could be implemented to avoid further damage. Systems functioning as AIAC transitions, for example automated emergency braking (AEB), have existed for a long time. The concept of AIAC transitions can be further explored in a wider variety of scenarios with increasing information from multiple sensors.

The situation awareness model from Endsley includes (1) perception, (2) comprehension, and (3) projection as three ascending levels (Endsley, 1995). This human factors construct defines how much people know before making a decision (i.e., the next cognitive step). After identifying the lack of research on cognitive processes during the take-over manoeuvre, we conducted studies (presented in Chapters 3 and 4) to obtain an understanding of situation-awareness rebuilding and the decision-making process before executing physical control. In these two studies, we expanded on techniques that have been previously used by Gugerty (1997).

Chapter 3 assessed the effect of viewing time and traffic complexity on situation-awareness; here, situation awareness was operationalized as the reproduction performance of the traffic situation in a top-down view. Considering basic configurations, such as the number of cars, position of the cars, and geometric similarities between placed and actual cars in the surrounding traffic, participants exhibited stationary situation awareness around 7 s. More time was needed for estimating speed, which seems to require up to 20 s. The results in Chapter 3 also showed that performances are highly situation-dependent, which means that providing a general recommendation of the time budget ahead of a take-over request would not be appropriate.

Chapter 4 included hazard situations to compare to participants' situation awareness levels and decision-making accuracy in non-hazard situations for different time budgets. The results showed no major differences in situation rebuilding performance between hazard and non-hazard situations. The exception was with 1-s situations: participants showed significantly worse situation awareness in 1-s hazard situations compared to 1-s non-hazard situations, which seems to be due to the weapon focus effect where the hazardous car attracts most of the attention. As for decision making performance, the decision accuracy was about 95% for non-hazard situations and only 75–80% for hazard situations in the 3 and 9 s videos. The difference could be due to the fact that selecting a decision from possible actions is more difficult in hazard scenarios. Thus, this finding demonstrates the difficulty of taking over in emergency situations compared to non-emergency situations. The associations between global

situation awareness (i.e., considering all cars on the road) or local situation awareness (i.e., considering only cars nearby) and decision accuracy were only weak to moderate. This could be because global situation awareness is irrelevant for avoiding a collision. As for local situation awareness, the weak-to-moderate effects could be due to time pressure: participants presumably relied on decision-making outside of conscious recall required during the rebuilding task. The notion of unconscious decision-making may also explain why fewer mistakes were made in the 'Evade left' scenario as compared to the 'Evade right' scenario. Summarizing, a clear relationship between explicit situation awareness (i.e., rebuilding performance) and implicit situation awareness (i.e., decision-making) is not evident from this study.

The main limitation of the studies in Chapter 3 and 4 is that the fidelity of the setups is low compared to actual on-road automated driving. However, our setup allowed for effective control of the traffic situation and of the temporal demands. Also, with the use of eye trackers in such controlled environment, we were able to show that participants exhibited similar scanning behaviour in the two PC-based studies (i.e., Chapters 3 and 4). People create an overview of the environment by distributing their viewing time between the front (i.e., front window) and back (i.e., rear-view mirror) equally in the beginning. Subsequently, the rear-mirrors viewing time decreases with elapsed time. In Chapter 4, we found that pupil diameter increased while approaching the hazard near the end of the video. However, the pupil diameter's sensitivity to light makes it difficult to apply on the road.

The SAGAT-type method which we used (Chapters 3 & 4) requires participants to consciously reconstruct the traffic situation. SAGAT is widely used in the research community, yet at the same time criticized (Endsley, 2015). Even though Chapter 3 and Chapter 4 have tried to capture the essence of situation awareness, we still have some recommendations for improvements with more resources. First, our setup was very simple and highly controlled as the drivers were answering what to do instead of executing actual control decisions. A more interactive experimental design could offer a more realistic view of the situation-awareness rebuilding process. Secondly, developments of real-time techniques for measuring situation awareness (i.e., instead of a freeze-probe technique) combined with a real-time eye-tracking system may provide more insight into the relationships between attention, object saliency, and situation awareness (Feldhütter et al., 2016; Gibson et al., 2016; Schmidt et al., 2016; Schömig et al., 2015; Zeeb et al., 2016). The use of a real-time algorithm

will offer opportunities for developing new applications, such as a driver monitoring system that relies on eye tracking.

The design of monitoring requests in Chapter 5 is realistic in terms of the availability of technology in automated driving. With HD maps and real-time traffic data, the vehicle could provide information that the upcoming situation is out of the operational domain of the automated driving system. The results of the experiment in Chapter 5 showed that MRs effectively direct drivers' attention to the road even if no physical control is needed. The participants subjectively appreciated this extra information. Moreover, monitoring requests improved the takeover time and quality in terms of braking behaviour in response to the take-over request that was provided after the monitoring request. The shortened reaction time can be expected to increase safety on the road.

Pedestrian crossings are not the only type of scenario that could benefit from monitoring requests. Based on HD maps and known functional limits of the automated system, merging and exiting segments of highways could be added to the list of scenarios. The time budgets for monitoring requests and take-over requests were fixed in our study, which could cause specific expectations about the timing of the pedestrian crossing scenario. The optimal length of time budgets would need more research; if the time budget for the monitoring requests is too long, drivers might lose their attention again after having received the monitoring request. Also, before actually implementing monitoring requests in cars, the long-term effects of this way of interaction would need to be studied. By means of road tests, it should be evaluated whether the compliance to monitoring requests lasts in the longer term, and if mode awareness is built up.

In the literature, the take-over request has been considered as the standard solution when encountering an automation disengagement (Zhang, De Winter, Varotto, Happee, & Martens, 2019). However, when and whether take-over requests should be triggered is not yet thoroughly investigated. Are all take-over requests necessary, or are they used too often to avoid responsibilities from the manufacturer? The cry-wolf effect (Bliss, 1993; Breznitz, 1983; Dixon, Wickens, & McCarley, 2007) caused by poor interface design will cause under-reliance and disuse. Another hazard is overreliance based on previous experience. Here, a failure of the take-over request, where the take-over request was not provided where it should have been, may contribute to accidents.

Looking at human factors developments history in aviation (Wiener & Nagel, 2010), I believe that human factor research will still have much more to offer to provide a safer path towards a automated driving future.

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LIST OF PUBLICATIONS

Journal papers

Lu, Z., Happee, R., Cabrall, C. D. D., Kyriakidis, M., & De Winter, J. C. F. (2016). Human factors of transitions in automated driving: a general framework and literature survey. *Transportation Research Part F: Traffic Psychology and Behaviour, 43*, 183–198. **(Chapter 2)**

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CURRICULUM VITAE

Zhenji LU

Born in JiXi, China, 31st December 1987.

Education

2014-2020   Delft University of Technology, The Netherlands

Faculty of Mechanical, Maritime and Materials Engineering,

Department of Cognitive Robotics

PhD in Human Factors (Recipient of Marie Skłodowska-Curie European Fellowship)

2013-2014   University of Warwick, United Kingdom

Warwick Mathematics Institute

Erasmus Mundus Joint Master of Science in Complex Systems Science

2012-2013   University of Gothenburg, Sweden

Faculty of Science, Department of Physics

Erasmus Mundus Joint Master of Science in Complex Systems Science

2010-2012   Harbin Institute of Technology, China

School of Astronautics,

Master of Science in Control Science and Engineering

2006-2010   Harbin Institute of Technology, China

School of Astronautics,

Bachelor of Science in Automation

Propositions

pertaining to the dissertation

Human Factors of Transitions in Automated Driving

Zhenji Lu

1. Most scenarios in 'take-over' research are invalid.

2. Questionnaires on experiences that respondents did not experience are useless.

3. The association between Situation Awareness and memory skills does not undermine the theory of Situation Awareness.

4. The measurement of human behavior in automated vehicles is valuable only if a properly designed HMI is used.

5. SAE Level 3 automation is a valley to go through, not jump over, for all automakers.

6. The SAE levels of automation are like stereotypes: bad but useful.

7. The presentation of scatter plots needs to consider trypophobia among readers.

8. Drivers' trust in automated driving technology needs constant calibration.

9. Safety is THE key issue in all automated driving developments.

10. The fact that PhD candidates in the Netherlands enroll as an employee instead of a student is beneficial to their mental health.

These propositions are regarded as opposable and defendable, and have been approved as such by the promotors dr. ir. Joost C. F. de Winter and dr. ir. R. Happee.