THE HUMAN FACTORS OF TRANSITIONS IN HIGHLY AUTOMATED DRIVING

by

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INTELLECTUAL PROPERTY AND PUBLICATIONS

The candidate confirms that the work submitted is his own, except where work which has formed part of jointly authored publications has been included. The contribution of the candidate and the other authors to this work has been explicitly indicated below. The candidate confirms that appropriate credit has been given within the thesis where reference has been made to the work of others.

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The work in **Chapter 2** of the thesis has appeared in publication as follows:
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The candidate contributed substantially to the conception and design of the study. The candidate collected, analysed, and interpreted the data, wrote the article, and approved of the version submitted for publication. NM and AHJ provided contribution in conception and design of the study, contributed to interpretation of data, and reviewed the manuscript. The candidate and NM gave final approval of the version submitted for publication.

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ABSTRACT

The aim of this research was to investigate the nature of the out-of-the-loop (OoTL) phenomenon in highly automated driving (HAD), and its effect on driver behaviour before, during, and after the transition from automated to manual control. The work addressed questions relating to how automation affects drivers' (i) performance in transition situations requiring control- and tactical-level responses, (ii) their behaviour in automation compared to in manual driving, (iii-iv) their visual attention distribution before and during the transition, as well as (v) their perceptual-motor performance after resuming control. A series of experiments were developed to take drivers progressively further OoTL for short periods during HAD, by varying drivers' secondary task engagement and the amount of visual information from the system and environment available to them. Once the manipulations ended, drivers were invited to determine a need to resume control in critical and non-critical vehicle following situations. Results showed that, overall, drivers looked around more during HAD, compared to manual driving, and had poorer vehicle control in critical transition situations. Generally, the further OoTL drivers were during HAD, the more dispersed their visual attention. However, within three seconds of the manipulations ending, the differences between the conditions resolved, and in many cases, this was before drivers resumed control. Differences between the OoTL manipulations emerged once again in terms of the timing of drivers' initial response (take-over time) in critical events, where the further OoTL drivers were the longer it took them to resume control, but there was no difference in the quality of the subsequent vehicle control. Results suggest that any information presented to drivers during automation should be placed near the centre of the road and that kinematically early avoidance response may be more important for safety than short take-over times. This thesis concludes with a general conceptualisation of the relationship between a number of driver and vehicle/environment factors that influence driver performance in the transition.

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ABBREVIATIONS

A number of abbreviations and acronyms are used throughout the this thesis. Although these are explained alongside their first instance in the text, they are listed here for ease of reference:

ACC	Adaptive Cruise Control.
ADAS	Advanced Driver Assistance Systems.
ANOVA	ANalysis Of VAriance.
ABS	Anti-lock Braking System.
AOI	Areas of Interest.
BASt	Bundesanstalt für Straßenwesen.
DOA	Degrees of Automation.
FAA	Federal Aviation Administration.
FCW	Forward collision warning.
HAD	Highly Automated Driving.
HMI	Human Machine Interface.
invTTC	Inverse Time To Collision.
LKS	Lane Keeping System.
NHTSA	National Highway Traffic Safety Administration.
OoTL	Out of the loop.
PRC	Percent Road Centre.
PERCLOS	Percentage Eye Closure.

SA	Situation Awareness.
SAE	Society of Automotive Engineers.
SD	Standard Deviation.
TOR	Take-Over Request.
TB	Time Budget.
TTC	Time To Collision.
TW	Time Window.

CHAPTER 1

GENERAL INTRODUCTION

1.1 Introduction

Vehicles with increasing degrees of automated capabilities will become ubiquitous in the coming decades, with vehicle manufacturers, technology start-ups, and giants alike having demonstrated interest and progress in the race to higher levels of vehicle automation. Indeed, many large vehicle manufacturers are already equipping production vehicles with lane keeping systems (Lincoln, 2014; Acura, 2014), traffic jam assistance (BMW, 2013) and highway steering assistance (Toyota, 2013; Volvo, 2013), and some manufacturers have committed to bringing the first generation of self-driving vehicles to market by the end of the decade.

Vehicle automation is proposed to have a number of benefits, including an increase in the flow and capacity of the road network (Kesting, 2008; Ntousakis, 2015), a wide range of economic benefits (Fagnant and Kockelman, 2013), an increase in shared mobility (Fagnant, 2013), and a reduction in energy consumption (Anderson et al., 2014). Human error is thought to be a contributing factor to over 93% of road accidents (Treat et al., 1979; Sabey and Taylor, 1980), and a further assumed benefit of vehicle automation is that, by relieving the human driver of parts of the driving task, human error would be suppressed, reducing road traffic accidents. Yet, this claimed benefit is potentially a red herring. Human error typically arises out of poor human-system interaction, because of a combination of active failures (e.g. drivers failing to detect a hazard) and latent conditions (e.g. the human-machine interface is designed poorly; Reason, 1990). Vehicle automation is in its infancy, and it will be some time yet until all human responsibility for, and interaction with, the driving task is supplanted, highlighting the paradox that automated systems will still be joint cognitive systems between man and machine (Bibby et al., 1975; Bainbridge, 1983). Therefore, while such interactions exist, so too does the possibility of human error and the importance of human factors.

To realise the full potential for vehicle automation for improving road safety, it is necessary to scrutinise how automation impacts on drivers' cognitive and physical abilities to interact safely and appropriately with the driving task (Parasuraman et al. 2000; Merat and Lee, 2012). A primary example of such an interaction is the resumption of manual control when the automated driving system either fails or reaches some functional limit, otherwise known as 'the transition'.

Indeed, there is a growing concern within the human factors community regarding the potential adverse effects of automation on drivers' return-to-manual performance. Studies have speculated that a number of psychological factors are pertinent to understanding the effect of vehicle automation on driver behaviour, including trust (Lee and See, 2004; Hergeth et al., 2016), locus of control (Stanton and Young, 2005), complacency (Bagheri and Jamieson, 2004; Parasuraman and Manzey, 2010), mental models (Moray, 1990; Sarter et al., 2007; Flemisch et al., 2012), driver state (Rauch et al., 2009; Neubauer et al., 2012; Jamson et al., 2013), mental workload (MWL; De Waard, 1996; Collet et al., 2003), and situation awareness (SA; Endsley, 1995a; Merat and Jamson, 2009; Kircher et al., 2014).

There have been some attempts to manage these issues during automation and the transition through, for example, adaptive automation disengagement systems (Merat et al., 2014) and haptic shared control (Abbink et al., 2012; Mars et al., 2014). Others have used uncertainty warning alerts (Beller et al., 2013; Lorenz et al., 2014) and multimodal human-machine interface (HMI) designs (Pavilinsky and De Winter, 2016). However, the effectiveness of these interaction designs is limited to the automated system and traffic scenarios in which the interactions are observed, all of which impose varying levels of mental workload.

Human factors research has developed a multitude of models to describe the driving task from the perspective of the driver. These can be divided into functional models and descriptive models. Functional models represent performance via various concepts such as motivation, information processing, and risk, and emphasise drivers' cognitive abilities, which give them greater predictive power, yet limit their descriptive depth. In contrast, descriptive models attempt to describe some or all aspects of the driving task with respect to the driver's role but are limited in their ability to predict performance. The following section will focus on functional models of human information processing to outline how this thesis conceptualises human performance for the driving task, while the subsequent section will focus on descriptive models to draw attention to the role of the driver in the driving task, and how this related to vehicle automation.

1.2 Understanding human performance

Information processing is the combination of psychological and motor processes that humans use to perform tasks. Implied in information processing theories is the concept of a limited processing *capacity* (e.g., Broadbent, 1958; Kahneman, 1973; Posner, 1978; Wickens, 1984). Kahneman (1973) specifies the metaphor of a single undifferentiated capacity from which mental resources are available for task performance, and proposed a serial processing model. On the other hand, Wickens (1984) introduced the idea of a multiple processing model, drawing a clear distinction between the metaphors of *capacity* and *resource*, defining capacity as the maximum or upper limit of processing capability, while resources represent the mental effort supplied to improve processing efficiency. Another critical assumption is that this capacity may also change according to whether the operator is fatigued or distracted, as using mental resources requires effort, and this is limited (cf. Malleable Resource Theory; Young and Stanton, 2002; Young and Stanton, 2004).

Wickens' (1984) information processing model builds on single resource theories (Kahneman, 1973; Norman and Bobrow, 1975), and presents a qualitative account of the different psychological processes involved in how humans interact with systems. The model incorporates these processes into a series of processing stages or mental operations to characterise the flow of information humans require when performing a task. This involves perceiving sensations, transforming data and choosing actions in response. Processing requires mental resources at each stage (see Figure 1.1). This is discussed further in Section 1.4.4.

Based on Wickens' (1984) model, information from the environment is first processed by our senses and is held briefly in the short term sensory story (STSS). What

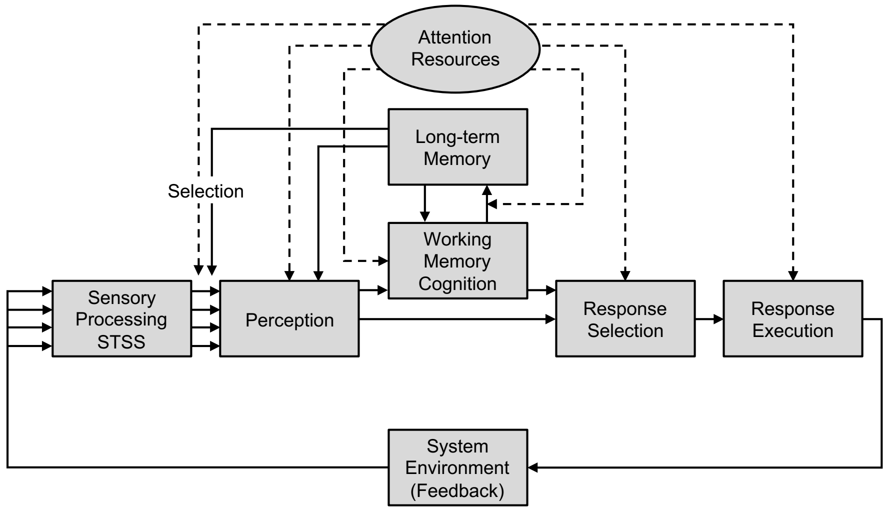


Figure 1.1: A model of human information processing (redrawn from Wickens et al., 2015, pg. 4).

is selected for sensory input is driven by attention (Yantis, 1998), either *bottom-up* (exogenous, stimulus-driven, or passive) or *top-down* (or endogenous or goal-driven or active). In the context of driving, information is most often selected and attended to overtly by directing the eye to its spatial location, demonstrating a close link between attention and eye movements (Posner, 1980; Crundall and Underwood, 1998).

Selected information from the STSS is then passed to stages of perception, where the stimulus is identified, or recognised using past experiences that are stored in the long-term memory, and it's meaning derived. This stage is processed automatically, requires little or no attention, and is driven by both sensory inputs and long-term memory. Following recognition, information is passed to response-selection and response-execution processes, where its implications for action are assessed, including the choice of a response. Otherwise known as cognition, this stage is distinguished from perception by the amount of time required to process information, as well as the mental effort involved.

As with most closed-loop feedback systems, this information processing system is in dynamic interaction with the external world and is driven by feedback signals and attention, which are essential for efficient human-automation interaction.

Questions have been raised regarding the efficacy of the information processing model, especially regarding its inability to explain and predict performance in low task-demand situations, such as monotonous driving (Senders, 1997). Nevertheless, it still stands as a useful, simple, framework for interpreting human performance in both simple and complex tasks.

With an understanding of how people process information to perform a task, the following section will focus on descriptive models of driving and the role of the human driver within the driving task.

1.3 Models of the driving task

Rasmussen's (1983, 1986) model of human behaviour in complex system control conceptualises tasks on the different levels of action selection and execution requiring the interaction between an operator and a task. The model categorises performance on three levels, namely *skill-based*, *rule-based*, and *knowledge-based* performance.

To take driving as an example, at the *skill-based* level a driver uses sensorimotor skills to process information in the form of space-time signals, such as vehicle handling around corners or driving along familiar routes. This represents automatic processing without conscious control. At the *rule-based* level, a driver processes information in the road environment (e.g. road regulations), which is then applied by feed-forward control. This represents conscious control. Cognitive functioning at the *knowledge-based* level involves drivers utilising mental models of the current roadway environment and vehicle state, integrated with their goals, to make decisions regarding navigation.

Michon (1985) conceptualised the three levels in Rasmussen's model regarding the skills and control of driving tasks and defined them according to the time involved in performing the task as well as the level of attentional control (Reason, 1987) given to the (sub-)task. At the lowest level, (*control level*) tasks involve the controlling of the vehicle's lateral and longitudinal position on the road through braking and steering. This level of a task occurs through automatic action patterns and within a time frame of milliseconds. The intermediate level (*manoeuvring level*) involves tactical decisions and manoeuvres by drivers to local situations, to achieve predetermined sub-goals, such as following distance, overtaking, speed, etc. These tasks occur in a matter of seconds. The advanced level (*strategic level*) involves drivers making and following goals of driving, such as navigating to a destination and also developing specific driving sub-goals, such as selecting a route. These generally take much longer to plan

Table 1.1: Matrix of driving tasks according to Rasmussen and Michon (Hale et al., 1990).

	Planning	**Manoeuvre**	**Control**
Knowledge	Navigating in strange town	Controlling a skid on icy roads	Learner on first on first lesson
Rule	Choice between familiar routes	Passing other cars	Driving an unfamiliar car
Skill	Home/work travel	Negotiating familiar junctions	Roadholding round corners

and execute.

Hale et al. (1990) mapped Rasmussen's performance levels to Michon's levels of driving behaviour, to specify the dynamic interaction among driver behaviour activities at different levels of the driving task (Table 1.1). Weller et al. (2006) presented a similar model (Figure 1.2), with performance levels according to Rasmussen (1986) shown on the left and the hierarchical control levels, according to Michon (1985), shown on the right. Ward (2000) argues that, within this framework, driving is modelled as a cascade system that includes input, output, feedback, and feed-forward processes. As a feedback process, driving goals at the strategic level cascade down and influence the behavioural responses at the tactical level, which in turn influence action-specific behaviours at the operational level (Ward, 2000). The feed-forward processes relate these levels to a hierarchical structure such that particular actions at the operational level make up those behaviours at the tactical level, and those behaviours are used to achieve the goals of driving, for example, arriving at a destination (Ward, 2000). However, it can be argued that automation removes or reduces drivers' feed-forward control of the driving task, which may, in turn, impair their ability to anticipate events on the road. Yet to what extent this impacts on performance in the transition to manual control at the different levels of driving, is still unclear.

By deconstructing the driving task into its constituent sub-tasks, we can better understand how changes to the relationship between the driver and the vehicle might affect the performance of the driving task as a whole. However, much of the focus in the literature has been on understanding the impact of automating various aspects of the driving task on, how, whether, and when, drivers regain control-level performance. Equally important is understanding how it affects drivers' recovery of adequate performance on the tactical and strategic levels.

These models consider the driving task as a three-way interaction between three

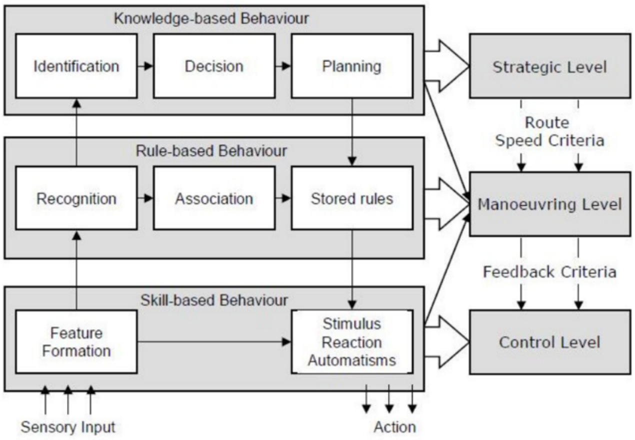


Figure 1.2: Combination of performance levels according to Rasmussen (1986) and the hierarchical control levels according to Michon (1985), reproduced from Weller et al. (2006).

agents, the driver, the vehicle, and the environment. However, it can be argued that an automated driving system is an additional agent introduced into these interactions. Changing the structure of the driving task in this way requires a reassessment of the driving model. While there have been multiple models seeking to describe the driving task itself, and others that integrate ACC (see Boer and Hoedemaeker, 1998), little objective research has been undertaken to establish the underlying cognitive mechanisms and mental models that drivers use to operate a highly automated vehicle, and how these mechanisms and models may be subject to decay. This is not altogether surprising as developing an accurate mental model of the dynamics of a system becomes increasingly difficult the more variables, and therefore interactions between them, are present within a system (Matthews et al., 2004). To understand the effects of automation on performance, the following section considers how humans interact with automation, both generally and in the context of the driving task.

1.4 Automation

In a contemporary sense, *automation* refers to

> "*the mechanisation and integration of the sensing of environmental variables (by artificial sensors), data processing and decision making (by computers); mechanical action (by motors or devices that apply forces to the environment), and/or "information action" by communication of processed information to people.*" (Sheridan and Parasuraman, 2005).

Applied to driving, the above describes how an automated driving system can perform some or all of the tasks or sub-tasks. Whereas in manual driving all sensing and control is carried out by the human, in current automated vehicles, drivers and their automated driving systems actively cooperate to achieve the primary task of driving, the success of which requires maintenance of a *shared situation representation/awareness* (cf. Christoffersen and Woods, 2002; Hoc, 2000; Stanton, 2016), *"appropriate" reliance* on the automated driving system (Lee and See, 2004), and *transparency* between the automated driving system and the human driver (Lyons, 2013). Strictly from the driver's perspective, this new and central role requires *supervisory control*[1], where the driver issues instructions with respect to the driving goals, which are then carried out by the automated driving system. Of course, the degree to which continuous supervision is required depends entirely on the capabilities and 'intelligence' of that particular system and the driver's experience with it.

1.4.1 Automated driving

The concept of automated driving was first presented in a 1925 New York Times article (New York Times, 1925), and was included in General Motors' vision of the future at the 1939 New York World's Fair (Geddes, 1940), and after realised in the GM Firebird Concept III, featuring automated steering (Electronic Chauffeurs, 1959). Many examples of the early concepts of automated vehicle concepts relied upon connection to some pre-existing road infrastructure (Guang Lu and Tomizuka, 2002). However, the 1980s and 1990s saw projects focused on developing the hardware and

[1]Elsewhere referred to as *human meta-control* (Sheridan, 1960) and *human supervisory control* (Moray, 1986; Sheridan, 1992a, Sheridan and Verplank, 1978)

software capabilities to enable automated vehicles to operate independently of any infrastructure. These included *Autonomous Land Vehicle (ALV)* (Schefter, 1985), which was funded by the Defense Advanced Research Projects Agency (DARPA), *Vehicle for Autonomous mobility thRough computer vision (VaMoRs)* (Dieckmanns, 1989), *Program for European Traffic with Highest Efficiency and Unprecedented Safety (PROMETHEUS)* (Williams and Preston, 1987), and *The Carnegie Mellon University Navigation Laboratory (NAVLAB)* (Goto and Stentz, 1987; Thorpe et al., 1991). However, some projects were still fully infrastructure dependent, for example, *Automated Highway Systems (AHS)*, run by the PATH Program at The University of California, Berkeley (Shladover, 2006). These projects were followed by three Challenges set by the DARPA: *Grand Challenge I* in 2004, *Grand Challenge II* in 2005 (Buehler et al., 2007) and the *Urban Challenge in 2007* (Buehler et al., 2009), which gave rise to a number of vehicles that were tested on public roads, including *Leonie* (Wille et al., 2010), *AutoNOMOS* (Rojo et al., 2007), and the *Google Car* (Markoff, 2010).

More recently, there have been a number of projects that have focused on the human factors issues related to vehicle automation, while also implementing and evaluating automated functions in vehicles, including *CityMobil* (Toffetti et al., 2009), *Automated Driving Applications & Technologies for Intelligent Vehicles (AdaptIVe)* (Langenberg et al., 2014), *Highly Automated Vehicles for Intelligent Transport (HAVEit)* (Hoeger et al., 2008), *Designing Dynamic Distributed Cooperative Human-Machine Systems (D3CoS)* (Zimmermann and Bengler, 2013), and *Kooperatives hochautomatisiertes Fahren, Cooperative Highly Automated Driving (KoHAF)* (ZENTEC GmbH, 2015).

1.4.2 Levels of automation

Over the years, several attempts have been made to create taxonomies or scales of the degrees of automation (DoA), otherwise referred to as levels of automation (LoA). Early versions, such as the widely used taxonomy presented by Sheridan and Verplank (1978, Table 1.2), are more general and typically account for the *locus of control* (human or automation) and how information is presented to the human. Parasuraman et al. (2000) later adapted the Sheridan and Verplank taxonomy to account for four stages of information processing (perception, analysis, decision-making, and execution) for each level of human-automation interaction. Contextualising a classification in this way allowed it to be used not only as a descriptor of human-automation interaction but also as a tool to choose appropriate LoAs for the relevant task. More application-specific taxonomies include Riley's (1989) model, which is applied to a mixed-initiative human-machine system, and Endsley and Kaber's (1999) model, which accounts for levels of human-automation interaction in real-time control tasks.

Table 1.2: Sheridan and Verplank's (1978) Levels of Automation.

	Description
1	Human does the whole job up to the point of turning it over to the computer to implement.
2	Computer helps by determining the options.
3	Computer helps to determine options and suggests one, which human need not follow.
4	Computer selects action and human may or may not do it.
5	Computer selects action and implements it if human approves.
6	Computer selects action, informs human in plenty of time to stop it.
7	Computer does whole job and necessarily tells human what it did.
8	Computer does whole job and tells human what it did only if human explicitly asks.
9	Computer does whole job and decides what the human should be told.
10	Computer does whole job if it decides it should be done, and if so, tells human, if it decides that the human should be told.

With the development of technologies bringing automated capabilities to the driving task, attempts have been made to understand human-automation interaction within the driving context. For example, Carsten and Nilsson (2001) sought to categorise different Advanced Driver Assistance Systems (ADAS) based on their functionality and proposed four broad categories: (1) systems that provide information, (2) systems that provide warnings or feedback, (3) systems that partly intervene, and (4) systems that facilitate autonomous driving. While specific to ADAS, such broad categories limit the value of Carsten and Nilsson's categorisation. Flemisch et al. (2008) provide a slightly different perspective, viewing the levels of driving automation by the extent to which the human or the system has vehicle control, as opposed to task-specific elements. In a similar approach, the German Federal Highway Research Institute (BASt) working group on automated vehicles developed a categorisation of automated driving functions (Gasser and Westhoff, 2012) as part of the work considering the Vienna Convention and German laws and regulations that may be a barrier for introducing automated vehicles in Germany. The BASt expert group identified five LoAs based on the degree of automation: full automation, high automation, partial automation, driver assistance, and driver only.

In parallel efforts, the National Highway Traffic Safety Administration (NHTSA, 2013) and The Society of Automotive Engineers (SAE, 2014) also developed classifications of driving automation. Similar to the BASt taxonomy in many respects, the NHTSA and SAE definitions describe, at each level of automation, what aspects of the primary driving task are performed by the human or the system (i.e. lateral control, longitudinal control, and monitoring), such that as the LoA increases, so does the role of the driver, shifting from a primary controller to a passive supervisor. However, recently the SAE LoAs (Figure 1.3) went further to explicitly delegate responsibility for monitoring the driving task and the road environment, with the driver being responsible for the lower levels (L0, L1, L2) and the system being responsible for the higher levels (L3, L4, L5). The SAE distinction rightly implies an automated driving system should have the capability to monitor the driving environment before it should be allowed to assume control of significant aspects of vehicle control.

This type of categorisation use by SAE has been criticised for implying a hierarchy of the technology, while its natural evolution is not likely to follow this exact path, which creates false expectations amongst policymakers, the press, and the public (Templeton, 2014). Nevertheless, the SAE levels of automation have since become the most widely cited vehicle automation taxonomy, and to standardise and aid clarity and consistency, the U.S. Department of Transportation (2016) adopted the updated 2016 SAE LoA definitions (SAE, 2016) in their Federal policy for automated vehicles. For these reasons, this thesis will adopt the SAE (2016) nomenclature.

At SAE Level 2 (L2, Partial Automation) and Level 3 (L3, Conditional Automation), the primary controllers of the driving task, longitudinal and lateral control, are automated via Adaptive Cruise Control (ACC) and Lane-Keeping Systems (LKS), respectively. This minimises the psychomotor aspect of control and modifies the cognitive element (Kircher et al., 2014), which fundamentally changes the role of the human in the driving task. In L2 systems, the emphasis on drivers' attention is shifted towards monitoring the driving task. In L3, drivers are not expected to monitor driving task but are expected to be available to make decisions and solve problems related to the driving task. In both systems, drivers are expected to be available to resume manual control should the system reach some limit. In the following section, we consider how this interaction most commonly manifests in HAD: the transitions of control.

SAE level	Name	Narrative Definition	Execution of Steering and Acceleration/ Deceleration	*Monitoring* of Driving Environment	Fallback Performance of *Dynamic Driving Task*	System Capability *(Driving Modes)*
Human driver **monitors the driving environment**						
0	No Automation	the full-time performance by the *human driver* of all aspects of the *dynamic driving task*, even when enhanced by warning or intervention systems	Human driver	Human driver	Human driver	n/a
1	Driver Assistance	the *driving mode*-specific execution by a driver assistance system of either steering or acceleration/deceleration using information about the driving environment and with the expectation that the *human driver* perform all remaining aspects of the *dynamic driving task*	Human driver and system	Human driver	Human driver	Some driving modes
2	Partial Automation	the *driving mode*-specific execution by one or more driver assistance systems of both steering and acceleration/ deceleration using information about the driving environment and with the expectation that the *human driver* perform all remaining aspects of the *dynamic driving task*	**System**	Human driver	Human driver	Some driving modes
Automated driving system **("system") monitors the driving environment**						
3	Conditional Automation	the *driving mode*-specific performance by an *automated driving system* of all aspects of the dynamic driving task with the expectation that the *human driver* will respond appropriately to a *request to intervene*	System	**System**	Human driver	Some driving modes
4	High Automation	the *driving mode*-specific performance by an automated driving system of all aspects of the *dynamic driving task*, even if a *human driver* does not respond appropriately to a *request to intervene*	System	System	**System**	Some driving modes
5	Full Automation	the full-time performance by an *automated driving system* of all aspects of the *dynamic driving task* under all roadway and environmental conditions that can be managed by a *human driver*	System	System	System	**All driving modes**

Figure 1.3: Description of Levels of Driving Automation for On-Road Vehicles Emphasising (A) Execution of steering and acceleration/ deceleration, (B) Monitoring of driving environment, (C) Fallback performance of dynamic driving task, and (D) System capability (SAE International, 2016).

1.4.3 Transitions of control

Regarding vehicle automation, the term "*transition*" has been used in the literature to refer to either the activation or deactivation of an automated driving function (Gold et al., 2013), a change in the level of automation (Merat et al., 2014), a transfer of responsibility (Saffarian et al., 2012), or the period between the changing from one vehicle control state to another (Flemisch et al., 2012). The term *transition* has also been used interchangeably in the literature with *handover*, *handoff*, and *take-over*.

In this thesis, the *transition* is defined as, *the process and period of transferring responsibility of, and control over, some or all aspects of a driving task, between a human driver and an automated driving system.*

While the SAE LoAs show the transitions that could occur between different levels of control (Figure 1.3), it is equally important to consider a framework delineating the principles of the transfer of control, which has been the subject of a number recent publications (cf. McCall et al., 2016; Lu et al., 2016). Here, we will focus on an ontology developed by Flemisch et al. (2008), outlining three basic principles of transitions.

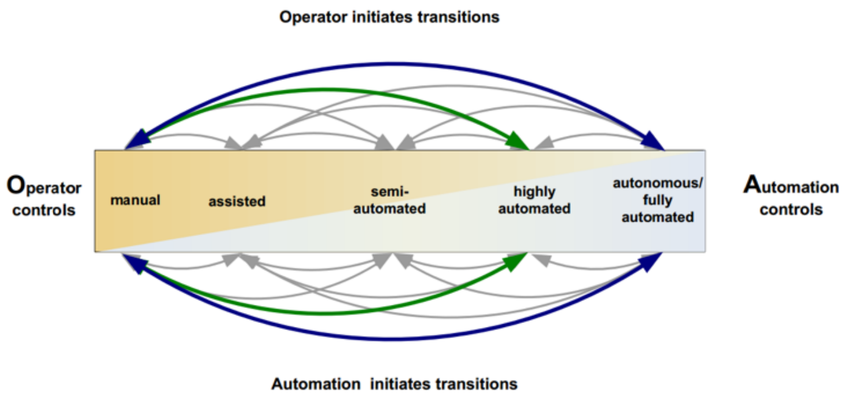


Figure 1.4: All possible transitions occurring between operator and automation at different levels of automation, with green arrows showing the transitions between manual control and highly automated driving, and the blue arrows indicating the transitions between manual control and fully automated driving (Flemisch et al., 2008).

The first principle relates to the direction in which a transition can occur, with Figure 1.4 showing control can be transferred from the driver towards the automated system, e.g. driver activating Adaptive Cruise Control, or transferred from the automated system towards the driver, e.g. system deactivation of a Lane Keeping System due to missing lane markings.

The second principle refers to who initiates the transition, the driver or the automated system. A driver-initiated transition, also referred to by Goodrich and Boer (1999) as a discretionary transition, might occur when the driver wants to take control because they feel their ability is rated as more expedient and safer. A system-initiated transition, otherwise referred to as a mandatory transition, is where the system has reached its limits either due, for example, to automation failure, road blockage, severe weather conditions, or sudden manoeuvres by another vehicle (Saffarian et al., 2012). However, there are also instances where system-initiated transition may be triggered in non-failure situations, for example, at the end of a programmed route.

The third principle considers who has control at the start of the transition and who is the recipient of the transition request.

Table 1.3: Transition of control from human to automation (redrawn from Martens et al., 2007).

	$\underline{\text{Hi}} \rightarrow \text{A}$	$\underline{\text{H}} \rightarrow \text{Ai}$	$\text{Hi} \leftarrow \underline{\text{A}}$	$\text{H} \leftarrow \underline{\text{Ai}}$
Who has "it"?	Human	Human	Automation	Automation
Who should get "it"?	Automation	Automation	Human	Human
Who initiates transition?	Human	Automation	Human	Automation

As part of the CityMobil project, Martens et al. (2007) proposed an ontology outlining the four different classes of transitions. The ontology is summarised in Table 1.3, with "H" referring to the Human and "A" to the Automation system. The underlined letters in the table specify who is in control, with the arrows representing the direction in which the transition is occurring, and the "i" defining which agent is initiating the transition.

Under baseline driving circumstances, drivers who are in safe manual control of a vehicle are assumed to have adequate levels of SA. In such a scenario, a driver-initiated transition from manual driving to HAD ($\underline{\text{Hi}} \rightarrow \text{A}$ and $\underline{\text{H}} \rightarrow \text{Ai}$) would be less complex from a human factors perspective, as the driver can choose whether to initiate, accept, or reject the transition request. Therefore, driver-initiated transitions are less likely to present a significant threat to safety than a transition HAD to manual control. The exception to this is if drivers assume that an attempted HAD activation is successful when it is not, and they mistakenly relinquish physical control.

In transitions from HAD to manual ($\text{Hi} \leftarrow \underline{\text{A}}$ and $\text{H} \leftarrow \underline{\text{Ai}}$), however, Endsley and Kiris (1995) argue that a system should have to consider driver state before relinquishing control, as drivers cannot be relied upon to guarantee they are sufficiently aware of the situation to ensure safe return-to-manual driving. Should the system be equipped with a driver monitoring system, the decision to relinquish driving control would have to be based on some empirical data of drivers' capacity and behaviour, in such conditions. For example, if the pattern of drivers' visual attention in the lead up to a transition shows that they were completely disengaged from the driving task, then a take-over-request could be delayed until drivers' attention is back on the driving task. Otherwise, the vehicle may initiate a minimum risk manoeuvre, bringing the vehicle to a safe position on the road. At present, this data does not exist. Therefore, it is further motivation to investigate drivers' capabilities and limitations in a research setting.

1.4.4 Human-automation interaction

Automation creates a trade-off between performance benefits and performance costs (Bainbridge, 1983; Sheridan, 2002). As seen in the aviation domain, as the degree of automation increases, there is an increased risk that performance following return to manual control will be degraded (Endsley and Kiris, 1995). A meta-analysis investigating the impact of degrees of automation (DoA) on human performance concluded that humans are much more vulnerable to automation "failures" when the DoA moves across the critical boundary from information acquisition and analysis to selecting and executing a particular action (Onnasch et al., 2013). However, these are conclusions drawn from observations of automation in control process tasks, such as traffic control tasks and unmanned aerial vehicle routeing tasks, and it remains to be seen if this relationship exists for vehicle automation.

Nevertheless, this apparent trade-off puts forward the paradoxical recommendation that, with increasing DoA, it is increasingly important that drivers are to some extent kept "in-the-loop", via decision and action selection as well as action implementation (Merat and Jamson, 2008). However, this argument is at odds with the espoused benefits of full automation, which would see drivers relieved of not only the driving task but also of managing or supervising vehicle automation. Also, classical vigilance studies (Mackworth, 1950) have shown that it is virtually impossible for an individual to maintain constant attention towards a source of information that does not often change, to monitor for any system changes, requests, or errors (Bainbridge, 1983). This limitation manifests as interaction errors and accidents, which have motivated much of the research on human-automation interaction (Wiener and Curry, 1980).

Mental workload and performance in the transition

One way to conceptualise performance in the transition is to consider it within the framework of mental workload (MWL) theory (Figure 1.5; De Waard, 1996), which follows the inverted-U function of the Yerkes-Dodson (1908) principle of optimal arousal. Mental workload is defined as "*the reaction to demand*", and "*the proportion of capacity that is allocated for task performance*" (De Waard, 1996). The model holds that

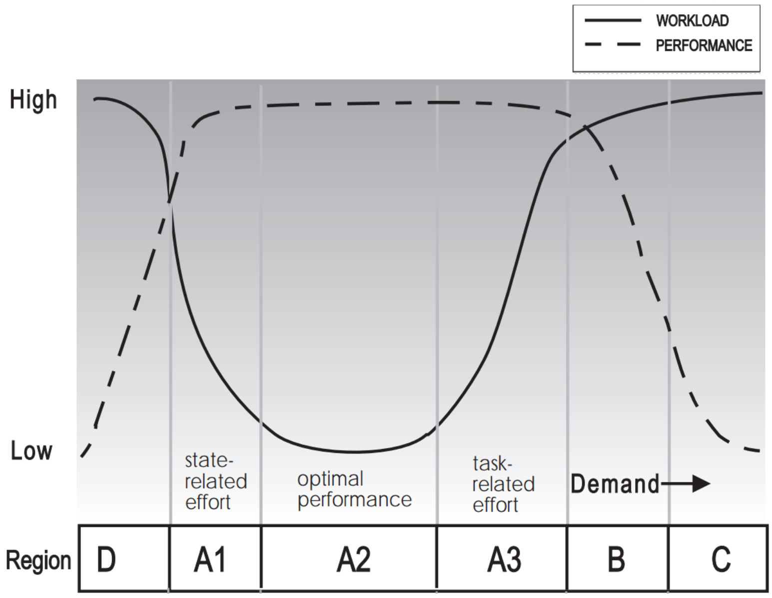


Figure 1.5: Workload and performance in six regions (De Waard, 1996).

conditions of extremely low task demand and under-stimulation (region D) will lead to decreased attention and diminished cortical arousal (Grandjean, 1979), which will result in low-performance efficiency. Performance is optimal in region A2, where the operator can easily cope with the task demand without changes to task performance. In regions A1 and A3, performance is not affected, but the operator has to increase effort to match task-demands. However, when task demands become too great, and task-related effort cannot be maintained, performance will decline (region B) until the high task-demand causes operator overload or fatigue, shown in region C, which results in low-performance efficiency (Hancock and Verwey, 1997).

Though the MWL model has been discredited on many fronts in terms of its ability to predict performance impairments (Matthews et al., 2000), task demand is a critical factor in the development of active and passive fatigue states, the latter of which would most likely be induced should significant aspects of the driving task be automated (De Winter et al., 2014). To illustrate the role of MWL on performance in the transition, let us consider an example from aviation.

The challenges presented by automation in aviation are in some ways analogous to those emerging in vehicle automation. For many years, aircraft have contained components that support the pilot by automating entire sub-tasks, including auto-throttle, anti-skid braking systems and flight management systems. Compared to ground vehicles, these can be likened to traction control, anti-lock braking system

(ABS) and forward collision warning systems (FCW). These systems are mainly aimed at supporting the safety intentions of the operator. However, it is the automated systems that assume some level of control over the aircraft that have created challenges regarding human-automation interaction, and not only concerning mode confusion and incorrect mental models of the automated system. Automating these aspects of the flying task does not necessarily reduce pilot workload, it simply transfers it to other tasks such as monitoring the system for errors (Parasuraman et al., 1996). During periods where workload demands are quite low, such as routine in-flight operations, pilots' monitoring behaviour has been shown to degrade (Sumwalt et al., 2002). This becomes most critical when a pilot is expected to rapidly direct 100% attentional effort to a task, due to a time-critical situation, such as during descent and final approach or if an automated system malfunctions or reaches a system limit. Here, the sudden increase in workload (moving from region A3 to B to C, in Figure 1.5), results in a concomitant decrease in performance, which manifests as poor decision-making or taking unsafe actions.

Similarly, should an driver who is disengaged from the driving task, be required to resume manual control from HAD, the mental demand for redirecting attention to both the cognitive and physical aspects of the driving task may also to lead to overload, especially for inexperienced or untrained drivers (Merat et al., 2012). Moreover, expecting a driver to monitor the automated system for long periods of time, while not being in control of the vehicle, can also lead to mental overload should the driver be unexpectedly required to attend to the driving task. Research in the aviation domain has also shown that the longer and more frequent a pilot uses automation, the more impaired their manual flight skills become (Wiener, 1988). The United States Federal Aviation Administration (FAA) acknowledged this in a recent Safety Alert For Operators (SAFO), discussing the findings of analysis done on flight operations, that there was an increase in manual handling errors (FAA, 2013). The report states, "*continuous use of auto flight systems could lead to a degradation of a pilot's ability to quickly recover the aircraft from an undesired state*". The SAFO recommended that operators incorporate "*emphasis of manual flight operations into both line operations and training*". It should not be taken lightly that the aviation industry is expressing such grave concern over the effects of automation, especially as pilots are typically more highly skilled, with more experience and operate in less complex environments than average drivers of ground vehicles.

However, a strict interpretation of performance from an MWL perspective assumes a set workload requirement during a transition, where in practice it is more dynamic. For example, traffic situations tend to change quite quickly. Therefore, there may be instances where drivers are asked to resume manual control, but as soon as doing so, any subsequent change in the road and traffic scenario may be associated with an increase or decrease in MWL for the driver. Therefore, it is also important to consider the effect of MWL in the transition in concert with the characteristics of both the transition and what drivers are doing before period of the transition.

While tasks requiring moderate MWL have traditionally been encouraged, to ward off the deleterious effects of underload and overload on attention (Hancock and Verwey, 1987; Schömig et al., 2015), in the context of transitions it is not clear whether this is sufficient to ensure a safe transition to manual driving, especially as task characteristics vary in terms of their stimulus attributes, conceptual criteria, goal states (what to do), and action rules (how to do it). It is clearly important, therefore, to understand the effect of different driver activities during automation on their ability to safely resume manual control. The following sections consider some factors known and hypothesised to influence drivers' performance in the transition.

1.5 Driver-based factors influencing performance in the transition

There is a range of factors contributing to the aetiology of automation-related interaction errors and accidents, including insufficient or inappropriate system feedback, misunderstanding of automation, and over-reliance on automation (Billings, 1997; Parasuraman and Byrne, 2003; Parasuraman and Riley, 1997). In addition, a number of inter-related psychological factors have been linked to drivers' capacity to interact safely with automated driving systems, including trust, mental models, situation awareness, and the out-of-the-loop problem (Young and Stanton, 2002; Merat and Jamson, 2009; Kircher et al., 2014; De Winter et al., 2015; Seppelt and Victor, 2016). These will be discussed below.

1.5.1 Trust

Automation trust can be described as *"the attitude that an agent will help achieve an individual's goals in a situation characterised by uncertainty and vulnerability"* (Lee and See, 2004, p. 51). Trust is an important factor determining the success of human-automation interaction, as it shapes users' willingness to rely on automation (Lee and See, 2004). However, it is equally important that users' develop *appropriate reliance*, as levels of trust that do not match the capabilities of the system, i.e. over trust or distrust, may lead to *misuse* or *disuse*, which are detrimental to safety (Parasuraman and Riley, 1997).

In their dynamic model of automation trust and reliance, Lee and See (2004) propose that trust is formed through a dynamic interaction between the automation, interface, operator and context, which is guided by three important elements: *First*, that trust and reliance are part of a closed-loop feedback process, where a user's trust in automation is guided by their reliance on it, and the user's reliance on the automation is in turn guided by their trust in it. The *second* element proposes that whether or not this trust translates into actual reliance depends on contextual factors such as user workload and effort to engage. *Third*, developing appropriate trust is highly dependent on how users' interpret information about the automation, and, therefore, the content and format of information displays are crucial to calibrating trust.

1.5.2 Mental models

For an operator to have effective control over any process, they must possess a mental model of that system (Johnson-Laird, 1980; Norman, 1983, Moray, 1990). A mental model is an operator's memory of a system, which is used to predict how or whether that system will respond to different control inputs and environmental changes (Klein and Crandall, 1995). The highest levels of situation awareness (Endsley, 1995a; see Section 1.5.3) are achieved when the controller can anticipate the future state of the system (Endsley and Kiris, 1995), and the accuracy of a mental model is related to their experience and training with that system, while its weakness may be caused by inconsistent system behaviours.

With the introduction of semi-automated driving systems, vehicle control and responsibility are shared between two agents, a driver and vehicle. A driver's mental model of that system's functionality will inform their decision about whether or not to intervene in particular situations. Should a driver's mental model be inconsistent with the *actual* system model, he/she may either intervene *unnecessarily* or worse, he/she may fail to intervene when it *is necessary* (Stanton and Young, 2000; Pauwelussen and Feenstra, 2011).

Therefore, mental models will play a crucial role in drivers' problem solving, judgement, decision making and abilities to plan and act, during their interactions with an automated driving system (Beggiato and Krems, 2013). It is of utmost importance, therefore, that drivers can develop appropriate models of the system's functionalities because both inappropriate intervention and active failure to intervene present a risk to safety (Sarter and Woods, 1995).

1.5.3 Situation awareness

Situation awareness (SA) is considered one of the most important of human factors constructs that are predictive of performance and safety (Parasuraman et a., 2008). Humans are highly adaptable, able to solve complex problems, and have a superior sensory system, making them highly capable drivers that can navigate effectively (Fletcher, 2008). However, for a human to fulfil these competencies in a driving context depends first and foremost on their awareness and understanding of the situation and environment.

What is situation awareness?

Several attempts have been made to develop a concise definition of SA, with Endlsey's (1988) being the most commonly cited:

> "*Situation awareness is the perception of the elements in the environment within a volume of time and space, the comprehension of their meaning, and the projection of their status in the near future.*"

Endsley (1995a) elaborated on this statement to define SA on three levels: Level 1 SA (*perception*) involves being aware of various elements of information in the environment

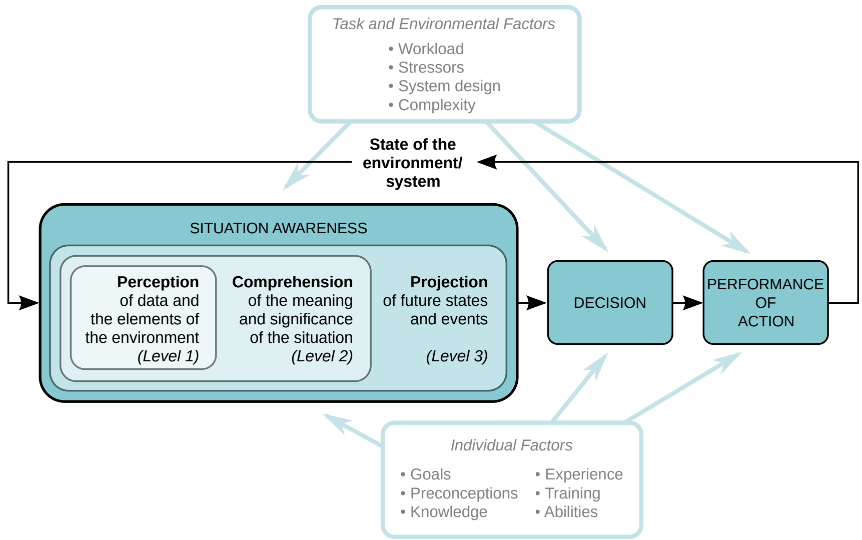


Figure 1.6: Endlsey's model of SA. This is a synthesis of versions she has given in several sources, notably Endsley (1995a) and Endsley et al. (2000), in Jin, 2008.

relevant to successful task performance, such as the size, colour, location and speed of objects. Level 2 SA (*comprehension*) refers to the ability to interpret the meaning, context and significance of that information, and is integrally linked to Level 1 SA. The third stage, Level 3 SA (*prediction*), refers to an ability to predict the future state or configuration of the environmental conditions, interpreted through Level 1 and Level 2 SA (Endsley, 1995a; Figure 1.6). SA does not only imply a driver knows what is going on, but that they know what is going on with elements in the environment specific to the driving task.

The levels of SA are hierarchically dependent, which means, for example, that a lack of visual cues and proprioceptive information at (Level 1 SA) will result in inaccurate meaning/sense making and prediction (Level 3 SA) (Ward, 2000). Conversely, an inaccurate prediction of future situations (Level 3 SA) can lead to a misinterpretation of the environmental context (Level 2 SA), which can lead to a false interpretation of specific elements in the environment (Level 1 SA). Therefore, in the same way, that the driving task requires both sufficient feed-forward and feedback elements to support task performance, and goal attainment, so sufficient SA on all three levels is necessary (Ward, 2000).

Assessing situation awareness

SA has been investigated in numerous domains, to investigate human performance, including military aviation (Endsley, 1995b), air traffic control (Endsley and Kiris, 1995), military operations (Matthews et al., 2000), driving (Walker et al., 2004) and the process industry (Hogg et al., 1995). Most researchers (e.g. Fracker, 1991; Sarter and Woods, 1995; Wickens, 1992) divide the measures for SA into three broad categories: (a) *explicit*, (b) *implicit*, (c) and *subjective* measures. *Explicit* measures require individuals to report material in memory, either *retrospectively* or *concurrently*, including freeze techniques, such as the well-known Situation Awareness Global Assessment Technique (SAGAT; Endsley, 1995b), which has been shown to have predictive validity. For example, in the aviation domain, Endsley (1990) showed that SAGAT scores were indicative of pilot performance in a simulation. *Implicit* measures utilise task performance to infer SA, which makes them objective and unobtrusive, but are limited in that poor performance may be as a result of factors other than low SA. Using *subjective* measures, such as the Situation Awareness Rating Technique (SART; Taylor, 1989), SA is assessed by self-assessment or by an observer. For example, Endsley et al. (2000) measured SA via real-time probes in an air traffic control task and found some relationship between SART and other SA measures but not SAGAT. While subjective measures are practical and easy to implement, they cannot be compared across raters, and scores may be skewed based on how good or bad operators perceived their task performance.

Despite the popularity of SA in the academic literature, there are some questions regarding its utility and scientific validity (Flach, 1995), with some accusing SA models of being limited by linear, information-processing theory, and providing a false distinction between cause and effect (Chiappe et al., 2011). Dekker and Hollnagel (2004), for example, described SA as a "folk model", lacking substance and offering no useful explanation of *how* failures arise, while Sarter and Woods (1995) note that precise definitions of SA are context-dependent, which limits its usefulness as a general theoretical concept. Endsley (2015) recently argued that many of these criticisms have arisen out of misconceptions or misunderstandings of the original Endsley (1995a) model. For example, Endsley (2015) argues that many researchers (e.g. Sorensen et al., 2010; Salmon et al., 2012; Dekker and Lutzhoft, 2004) incorrectly state that the levels of SA in Endsley model, are linear, where they, in fact, represent ascending levels of SA. She went on to rebut these and other 'fallacies' by referring to a strong body of empirical work supporting SA as a diagnostic tool for different humans states, and as a useful prescriptive model. Next, we consider research focused on the assessment of SA in HAD.

Situation awareness in HAD

In a critical review of the literature, De Winter et al. (2014) argued there is a close link between HAD and SA, based on studies of drivers' eye movements, tests of object detection, engaging in tasks unrelated to driving, and responses to critical incidents. With regards to eye movements and tests of object detection and comprehension, there is an assumption that if a driver is scanning the road environment, they will have better SA. For engaging in tasks unrelated to driving, there is an assumption that increased engagement in these tasks will mean lower SA, while for responses to critical incidences, there is an assumption that the better the responses, the better the SA.

Eye movements In terms of drivers' eye movements, a few studies (e.g. Carsten et al., 2012; Damböck et al., 2013) have found that, compared to manual driving, drivers in HAD were overwhelmingly less likely to monitor the road, especially the centre of the visual field, where accidents are more likely to occur. Carsten et al. (2012), for example, found that, for the 24 drivers who did not focus on the DVD player during HAD, their visual attention was concentrated on the central region of the road only 53% of the time, compared to 72% in manual driving. While these results do not necessarily allow us to conclude specifically on maintenance or loss of SA, they do give some indication that drivers under automation are more inclined to lose SA for the driving task/environment during HAD, only because they are not monitoring the driving task. Moreover, it is well established that the more visual attention is paid to the road scene so the potential for higher SA increases (Green, 1999; Chaparro et al., 1999), therefore, it follows that the reverse would also be true. However, few studies have examined eye gaze behaviour for drivers with varying levels of engagement with the driving task during HAD, which is pertinent given the range of different tasks/activities that drivers could engage with during automation.

One example is that of Merat et al. (2014), who analysed drivers' reaction times after automation disengaged automatically if they were not looking at the road centre for longer than 10 s. The authors found that there was a 10-15 s lag time between when automation disengaged and drivers' resuming of control. In another driving simulator study, Gold et al. (2013) showed that, in-between a take-over request and resumption of control, drivers tended to fixate on side mirrors, which suggests that this time is used regain SA *before* resuming control. Lorenz et al. (2014) reporting that drivers are quick to direct visual attention to the road scene but struggle to instantly understand the situation. However, the precise eye movement patterns underlying the process of SA recovery in the transition for drivers with varying levels of SA is not clear, and deserve further investigation.

Tests of object detection There are conflicting conclusions regarding the impact of vehicle automation on driver SA when based on tests of object detection. For the most part, these discrepancies can be attributed to differences in methodological approaches and interpretation of SA results. For instance, in their meta-analysis of SA and HAD, with tests of object detection and comprehension, De Winter et al. (2014) analysed studies by Davis et al. (2008) and McDowell et al. (2008) and concluded that HAD can result in improved SA compared to manual driving, as drivers in HAD were able to detect more targets in the road scene. It is curious, though, that the authors drew this conclusion for SA in HAD, as the studies were on military convoy drivers that had to detect targets in the road scene, and not anything pertaining to the environment related to the driving task. It is incorrect to conclude on SA if the task used to measure it does not in any way form part of what is being investigated in the first place. The object detection task was not related to performance in the driving task and, therefore, it is tenuous to assume that maintaining SA in one task implies a maintained SA in another. Other studies have come to different conclusions on SA. Biondi et al. (2014) used a surprise recognition memory task developed by Strayer et al. (2003), to assess the impact of automation on SA during a drive, which is an *explicit retrospective* measure of SA. Using a between-subjects design, the authors found that drivers in HAD were able to recall fewer detailed features in the environment than those in the manual driving group. This is an interesting means to probe SA without imposing additional workload during the task. Its utility is limited, however, as participants may intentionally memorise features in the road scene if they suspect they might be asked about these at a point in the future. Moreover, it is difficult to draw conclusions on task-specific SA with a metric designed to assess general SA.

Non-driving related activities There is a consensus in the literature that HAD encourages higher uptake of non-driving related activities, compared to manual driving. Carsten et al. (2012) report that, during HAD, drivers were more likely to use a DVD player than during manual driving (32.5% vs 2.6% of the time) and also more likely to use the radio (54.1% vs. 41.4% of the time) and even read a magazine (9% of the time). This is confirmed by other studies, with Llaneras et al. (2013) finding that, during HAD, half of the participants texted or emailed during a 1.5h-2h drive. The authors found that participants engaged in a number of other tasks during HAD including eating, reaching for an item in the rear compartment, dialling and talking on the cell phone. The fact that drivers chose to partake in tasks unrelated to driving does not necessarily reflect the extent to which SA has been lost, or indeed that they have impaired SA at all. As with measures of eye movements, it simply gives an indication of the extent to which SA could possibly be lost. A further limitation of this method is that the authors do not link the type of reaction to any safety or performance-related outcomes, which would be useful to form a holistic view of the importance of SA to performance in the transition.

Reactions to critical events Measuring drivers' reactions to critical events while in HAD has become a standard methodology for the assessment of the impact of HAD on performance. As part of the CityMobil project, Merat and Jamson (2008) examined driver reactions to a number of 'critical' incidents, including merger from the left, an oncoming car turning across the vehicle path, the presence of traffic lights, and the presence of a parked car. Drivers' responses in manual driving were compared to those in HAD, where a critical incident triggered automation disengagement and the driver was expected to respond. The authors used a measure of 'anticipation', defined as drivers' ability to predict and understand the behaviour of traffic during these critical events, to conclude on drivers' SA. Anticipation was measured as the difference in time between the lead car's brake lights coming into sight and when drivers depressed their brake pedal. Results showed that, for the three longitudinal critical events, drivers in the automated driving condition braked on average 1.5 s later than in the manual driving condition. In the lateral critical event (parked car), 28 of the 38 drivers in the automated driving condition braked after the collision warning alarm was emitted. One possible explanation is that drivers were less aware of the unfolding events. However, the authors suggest it may also be because drivers over-relied on the automated system, concluding that the use of an automated driving system may reduce drivers' situational awareness and may also cause drivers to become complacent behind the wheel.

While it is possible to make inferences about the state of drivers' SA, there are a number of factors in the design of these critical events which can influence how drivers react. These include the time budget within which a driver is required to resume control, the road and traffic scenario and the way in which automation status and take-over request is communicated, and are discussed in Section 1.6.

1.5.4 The out-of-the-loop problem

A key underlying factor contributing to the issues outlined above is the out-of-the-loop (OoTL) performance problem (Kaber and Endsley, 2003). According to Kienle et al. (2009), a driver is considered OoTL when they are "*not immediately aware of the vehicle and the road traffic situation because they are not actively monitoring, making decisions or providing input to the driving task*". Therefore, OoTL refers to a state where an operator loses awareness of the system state and external situation due to limited human-system interaction (Endsley and Kiris, 1996). This is typified by a reduced ability for an operator to re-enter the system control loop and resume manual control. In this sense, OoTL pertains more to the state of the system than the state of other elements in the environment, which is the focus of SA. However, these are not mutually exclusive. In the first instance, humans are poor supervisors and therefore not efficient at detecting system errors (Parasuraman and Riley, 2007). Also, in the event of an automation failure, the time it would take to re-orient an OoTL operator to both the system state and the task at hand would most likely result in either a diminished effectiveness of the task or even a total failure to complete the task (Kaber and Endsley, 2003). The concept of an OoTL state offers an insight into the performance consequences of automation. However, it does not incorporate aspects related to automation-induced complacency and automation bias, which plays a key role in the development of the OoTL state (Parasuraman and Manzey, 2010).

1.5.5 Complacency and automation bias

Parasuraman and Manzey (2010) describe complacency as an attention allocation strategy, where automated tasks are neglected in favour of manual tasks, and which is comprised of trust, confidence, reliance, and safety-related complacency (Parasuraman et al., 1992). Automation bias, however, refers to omission or commission errors made by operators, essentially a tendency towards over-reliance on automation (Parasuraman and Manzey, 2010). These phenomena highlight issues with imperfect automation and help explain why drivers might experience difficulties when automation does not function as it should. To better understand these regarding performance consequences, Parasuraman and Manzey (2010) developed an integrated model of complacency and automation bias (Figure 1.7).

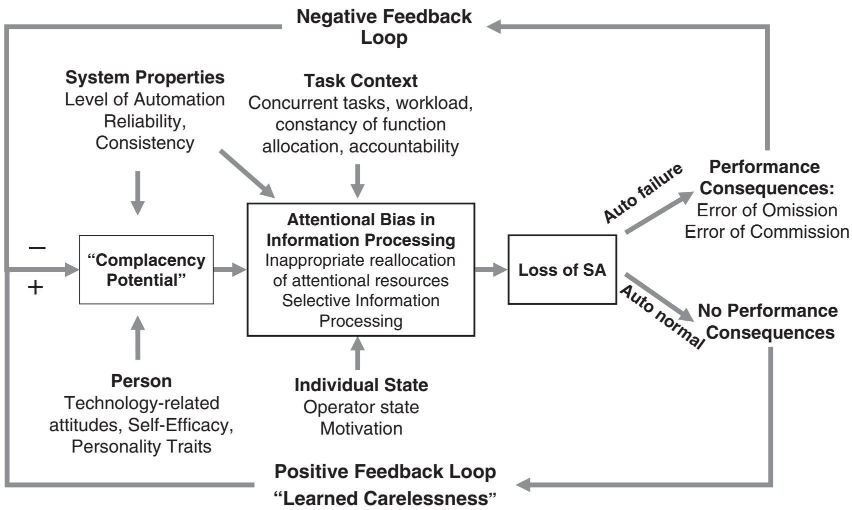


Figure 1.7: An integrated model of complacency and automation bias (Parasuraman and Manzey, 2010).

The model consists of three critical features: 1) it distinguishes between two aspects of complacency and automation bias, referred to as "*complacency potential*" and "*attentional bias*" in information processing (Singh et al. 1993a, 1993b), 2) the differentiation between automation-induced attentional phenomena and its possible performance consequences, and 3) two feedback loops reflecting the dynamic and adaptive nature of complacency and automation bias (Manzey and Bahner, 2005). The authors conceive complacency potential as a tendency to react in a less attentive manner when interacting with a particular automated system, which is influenced by system properties (e.g. perceived reliability and consistency) and also individual characteristics of the operator (e.g. attitudes and personality). These factors are thought to have a much stronger influence over complacency when task load is high and, therefore, related to attentional bias (task prioritisation and allocation of attentional resources). These two phenomena lead to the loss of SA, which manifests as a performance consequence should automation fail, but has no direct performance consequence if automation functions normally (Parasuraman and Manzey, 2010).

The presence of positive and negative feedback loops in the model implies that performance consequences are not due to a lack of appropriate system competency or knowledge. While the model does account for the influence of an individuals' state on attentional bias, the authors provide no explanation for how different operator and motivational states might affect performance consequences. So while the model provides a coherent account of the role of complacency and attention bias in the loss of SA, and, therefore ,performance consequences, it is limited in its ability to account for the exact role of drivers' engagement with the driving task, nor does the original description of the OoTL phenomenon, described in the previous section. A possible solution to this shortfall is to combine these concepts to form a view of interaction regarding different levels of engagement with the driving task.

For instance, Banks and Stanton (2014) used previous work on human-automation interaction to theorise four states of engagement with a driving task, across a combination of in/out-of-the-loop and active/passive states (Table 1.4). While plausible, the authors provide no empirical results to validate these different states concerning HAD. They also only refer to driver state regarding the driving task and make no mention of the impact of arousal on these states. For instance, the Out-of-the-loop & Passive state does not distinguish between a driver who is cognitively engaged in a non-driving related task and one who is mind-wandering. Moreover, tasks vary widely regarding their cognitive, visual, and auditory loads. Therefore, if interacting with automated driving systems could give rise to these different states of engagement, then it is vital to establish exactly what these are and what their implications are for a drivers' ability to resume control. This is key to developing appropriate strategies for ensuring drivers safely and efficiently re-engage in manual driving. For example, human-machine systems that emphasise either situation-relevant information or haptic vehicle control support during the transition, or both.

Table 1.4: States of engagement with a driving task (Banks and Stanton, 2014).

	In-the-loop	Out-of-the-loop
Active	The driver is in full control of the vehicle and actively engaged in the driving task.	The driver is in full control of the vehicle but showing characteristics of being out-of-the-loop e.g. driving without attention.
Passive	The driver is no longer in control of the vehicle but remains vigilant to the driving task.	The driver is no longer in control of the vehicle and becomes desensitised to the driving task.

1.6 Vehicle/Environment-based factors influencing performance in the transition

There are a number of vehicle/environment-based factors shown to influence driver performance in the transition, including the transition time budget, the design of the HMI, and the road and traffic situation.

1.6.1 Time budget

A primary area of interest in the study of transitions in HAD in recent years is the time it takes for drivers to resume manual control given a particular time budget or lead time (e.g. Damböck et al., 2012; Gold et al., 2013; Naujoks et al., 2014; Zeeb et al., 2015; Payre et al., 2016). Damböck et al. (2012) was the first to systematically vary the time budget available to drivers following a take-over request. Comparing time budgets of 4 s, 5 s, 6 s, and 8 s, the authors found that, compared to when in manual control, drivers crashed significantly more frequently in all time budget conditions except for the 8 s condition. Gold et al. (2013) examined driver behaviour following an auditory take-over request at either 5 s or 7 s time-to-collisions, with a stationary vehicle in the lane ahead. Results were compared to a baseline group that performed the same task but in manual driving. The Gold et al. study provides a detailed account of behavioural responses to different take-over times (see Figure 1.8). Drivers with a shorter time budget (5 s) were able to react faster in all considered variables compared to drivers given a longer time budget (7 s), but they tended to have fewer glances at the rear and side mirrors before a lane change and were also less likely to use an indicator. Therefore, drivers who were given a 5 s time budget showed more erratic

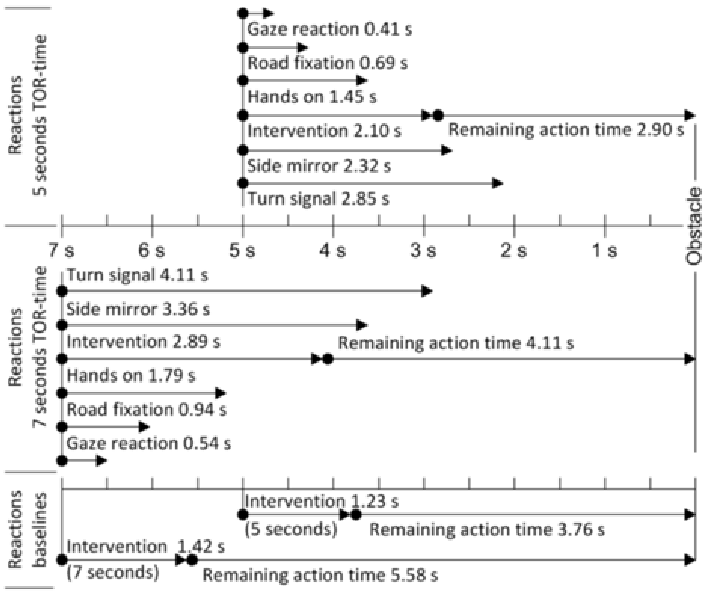


Figure 1.8: Reaction sequences in the Gold et al. (2014) study.

behaviour following a take-over.

Using a similar rear-end near-crash situation, van den Beukel and van der Voort (2013) found that, when given time budgets of 1.5 s and 2.8 s, drivers in in 47.5% and 12.5% of cases, respectively, were unable to avoid colliding with a braking lead vehicle. Zeeb et al. (2015) found similar crash rates, where 45% of drivers who were given a time budget of 4.9 s crashed with a lead vehicle, and where 15% of drivers given a 6.6 s time budget, crashed. These studies clearly demonstrate that, in time-pressured take-over scenarios, drivers struggle to resume vehicle control and resolve the critically of the situation.

However, the motivation of focusing on driver responses given different time budgets arises from a need to define operational and technical parameters for the design of automated driving systems, which, as pointed out by Larsson (2013), provides only a narrow view of how drivers interact with their automated driving system. This is especially true considering that some other external factors in the transition scenario vary between studies. This limits our understanding of deeper behavioural adaptations brought about by such system interactions, and, therefore, how they should be designed to ensure safe and efficient interactions.

1.6.2 Human-Machine Interface (HMI)

The Human-Machine Interface (HMI) is used to provide system feedback to users, which is argued to be important for appropriate human-automation interactions (Norman, 1990). Incorrect or insufficient system feedback could result in drivers developing inaccurate mental models, which could lead to errors in decision or action (Sarter and Woods, 1995). To ensure that feedback is both correct and sufficient, Norman (1990) proposed a set of four design criteria for automation HMIs, as follows: "*Appropriate design should (1) assume the existence of error, (2) it should continually provide feedback, (3) it should continually interact with operators in an effective manner, and (4) it should allow for the worst of situations*" (Norman, 1990).

The design of feedback and warning systems for automated vehicles typically communicate information in range of modalities (for a review, see Manca et al., 2015), sequences (Radlmayr et al., 2014), and with various meanings (Lorenz et al., 2014; Beller et al., 2013).

The nature of the HMI has been shown to have some mediating effect on performance in the transition. For example, concerning modality, Naujoks et al. (2014) assessed driver performance following 'visual' and 'visual + auditory' take-over requests in three different traffic scenarios. Reaction time, measured as hands on the steering wheel, was significantly higher for the 'visual' group compared to the 'visual + auditory' group (6.19 s vs. 2.29 s). Similarly, both maximum lateral position and SDLP were significantly higher for the 'visual' group compared to the 'visual + auditory' (0.84 m vs. 0.43 m and 0.30 m vs. 0.15 m, respectively). Differences between modality conditions were more pronounced the more difficult the traffic scenario. Lee et al. (2002) found that an auditory warning elicited significantly shorter braking times, irrespective of whether participants were distracted or not.

Petermeijer et al. (2015) investigated the usefulness of vibrotactile stimuli embedded in drivers' seats to elicit faster take-over time. The authors found that, when the vibrations were presented in a static pattern, steering wheel touch and steering input reaction times were approximately 200 ms faster than when presented in a dynamic pattern, which indicated a directional cue for a lane change manoeuvre However, the study did not include a non-vibrotactile condition against which to evaluate the usefulness of vibrotactile warnings.

Lorenz et al. (2014) investigated two augmented reality (AR) concepts for warnings and information during the transition. An "AR red" concept projected a restricted corridor directly onto the road scene, showing the driver where they must not steer through, while an "AR green" concept displayed a safe corridor showing the driver where they can steer through, and a control condition provided no AR information. There was no difference between the two concepts regarding take-over time. However, drivers in the "AR green" concept had better vehicle control, as measured by steering trajectories, and longitudinal and lateral accelerations.

In a driving simulator study, Beller et al. (2013) used symbols of automation uncertainty in an attempt to improve driver-automation interaction. The authors compared the use of automation uncertainty versus no uncertainty information in high and low automation reliability conditions and found that displaying automation uncertainty increased time-to-collision in the case of automation failure. These studies confirmed the importance of system feedback during the transition in improving not only performance but also acceptance of and trust in the automated system.

1.6.3 Road and traffic scenario

There are some road and traffic situations that have been investigated in studies of the transition and typically reflect actual or predicted limitations or boundaries, of an automated driving system. These include situations where the vehicle is reaching a target destination, surrounding vehicles or road works obstruct intended journey path, technical/sensor failure, and a system limitation in dealing with unaccounted for road and traffic scenarios, such as an accident or absence of road infrastructure supporting the automation.

Radlmayr et al. (2014) investigated the effect of varying traffic situations and non-driving related tasks on the process and quality of a system-initiated take-over. The experiment was conducted in a high-fidelity simulator and used the standardised visual Surrogate Reference Task (SuRT) and the cognitive n-back task to simulate the non-driving related tasks. The study included four traffic situations each with a time budget of 7 s: In situation No. 1, an obstacle appeared in the middle lane, while the right and left lane were blocked by vehicles at the time of the take-over request (TOR). In situation No. 2, an obstacle appeared in the right lane while no other vehicles were present during the situation. In situation No. 3, the obstacle appeared on the left lane. Situation No. 4 closely resembled No. 1, except that the two adjacent lanes were not blocked. The authors used a range of dependent variables to infer quality of the transition. These included take-over time, longitudinal acceleration, time to collision (TTC), the total number of collisions during take-over, results from a Detection Response Task (DRT) and the subjective rating. The authors concluded that traffic scenario and traffic density had a substantial effect on take-over quality in a highway setting. Similarly, Kircher et al. (2014) found that drivers' response times were moderated by whether the driver was pre-warned and by the type of scenario. Traffic density has been shown to influence how long drivers need to regain situation awareness and resume control (Jamson et al., 2013; Gold et al., 2016). These suggest that performance in the transition is dependent on the complexity of the traffic scenario. However, Naujoks et al. (2014) found no effect of traffic scenarios in a take-over event.

1.7 Summary and key research gaps

Impaired performance during in human-automation interaction is typically attributed to the *out-of-the-loop (OoTL) phenomenon* (Endsley and Kiris, 1995). However, depending on the context, the term *"loop"* has been used to refer to one of a range of factors, including varying degrees of physical control, cognitive control, awareness, and feedback. Moreover, it may be concluded that some of the key gaps in our knowledge on how drivers interact with automated driving systems can be defined in the following broad terms:

- With the appeal of automation to free drivers' attention in the vehicle, the research community has focused on understanding the impact of engagement in one or two non-driving related secondary tasks at a time, on behaviour and performance. However, given the importance of SA to safe human-automation interaction, it is notable that little research has compared the effects of a range of conditions that systematically vary the impact of drivers' SA during automation to investigate drivers' performance during the resumption of manual control.
- A common approach in assessing driver behaviour during automation is to

employ metrics traditionally used in the study of manual driving, which, as discussed in the following chapters, often fall short of what is necessary to quantify not only *how* drivers interact with automation, but also the *quality* of that interaction. It may be concluded that there has been no consistently applied objective measure of the quality of performance after the transition. SAE International (2014, p. 7) states that performance is taken to be "*the timely, safe, and correct performance of the dynamic driving task for the prevailing circumstances*", yet quite how studies define this is either scarcely reported, and varies widely. Some studies have focused on take-over time as a measure (Gold et al., 2014), while others have considered minimum time to collision (TTC; Gold et al., 2013), minimum time headway (Merat and Jamson, 2009), and maximum accelerations (Zeeb et al., 2016; Hergeth et al., 2016). However, take-over time and other response-time based measures do not detail the quality of vehicle control following the transition, and while this can be described in part by TTC and vehicle-based measures, their interpretation is somewhat constrained by the kinematics of the scenario. Therefore, a deeper understanding of how these performance measures should be interpreted in the context of the transition is required.

Clearly, these issues have contributed to the research community's inability to concur on a definition of an out-of-the-loop driver, how this state is assessed and classified, and what behavioural response profiles reflect an efficient and safe transition to manual control. If we can understand the nature of the OoTL performance problem, and how this interacts with SA, we will be better able to predict performance breakdowns in different situations, which will inform the design of more human-centered automated driving systems that augment drivers' capabilities and mitigate their limitations.

1.8 Research questions and thesis overview

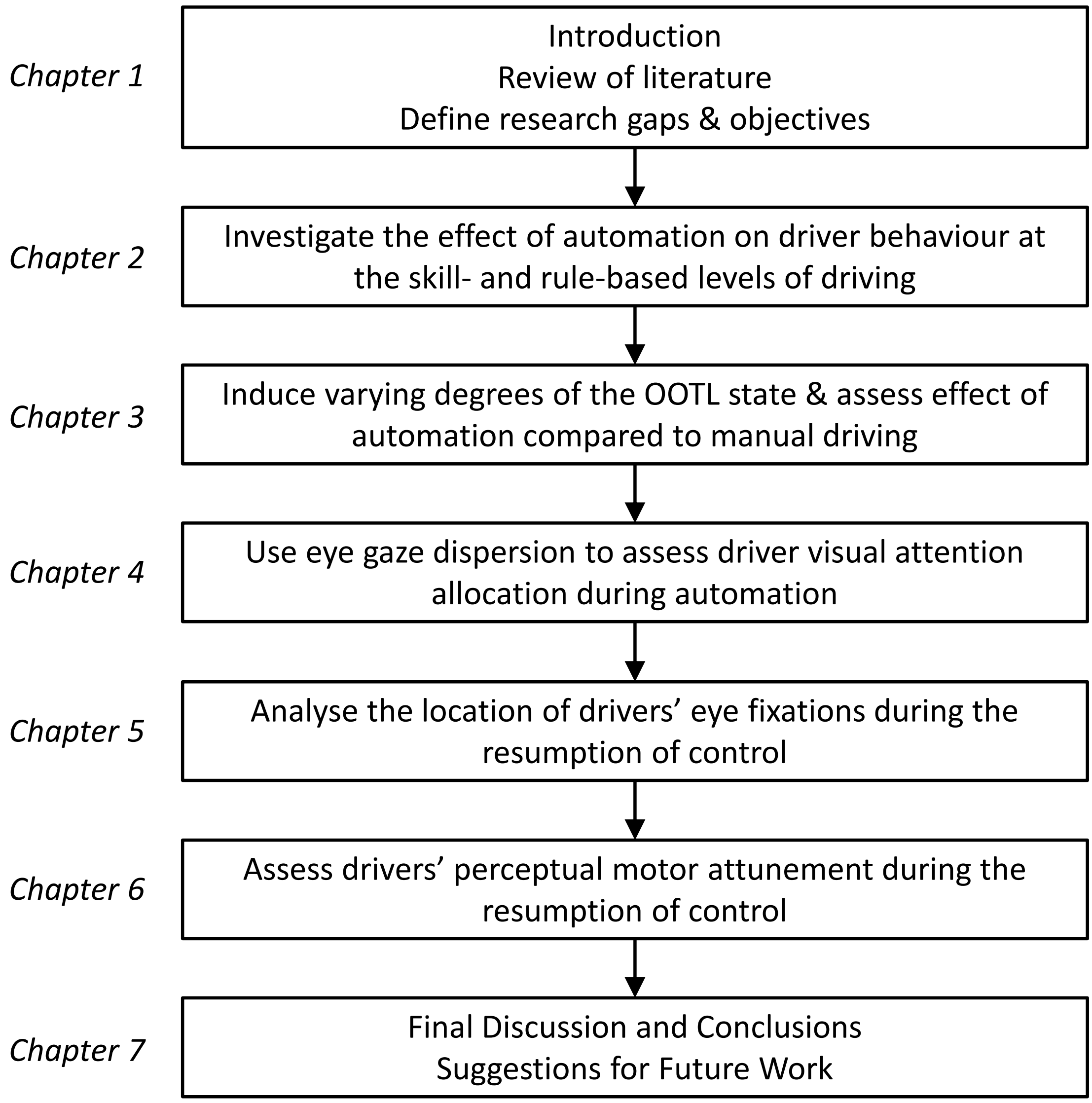
The aim of this thesis is to investigate the nature of the out-of-the-loop phenomenon in highly automated driving, and its effect on driver behaviour during automated driving and the transition from automated to manual control. In particular, the thesis seeks to address the following questions:

1. **How does automation affect drivers' performance in transition situations requiring control- and tactical-level responses?**
2. **How does automation affect drivers' behaviour in automation compared to manual driving?**
3. **What is the pattern of drivers' visual attention distribution during automation?**
4. **How does automation affect drivers' visual attention distribution in the transition?**
5. **How does automation affect drivers' perceptual-motor performance during and immediately after the transition?**

To induce a range of OoTL states during HAD, drivers were exposed to various OoTL manipulations. These manipulations varied regarding drivers' secondary task engagement as well as the amount of visual information available to drivers from the system and road environment.

As outlined in Figure 1.9, the overall structure of the study takes the form of seven chapters.

Figure 1.9: Thesis structure.



- **Chapter two** reports on a study that sought to establish a realistic highway use-case for studying human-automation interaction, as well as a methodology to probe drivers' ability to respond to critical road events following the resumption of control from automation. To vary driver workload during the transition while maintaining the same use-case, drivers were given directional cues for a lane change manoeuvre, based on the colour of the lead vehicle.

- **Chapter three** details the refinement of the use-case, and reports on the development of a series of experimental conditions designed to induce varying degrees of driver engagement and interaction with the driving task (OoTL manipulations). Using analysis of eye gaze dispersion, it goes on to discuss how each condition affects driver information needs during automation and the transition of control.

- **Chapter four** presents the analysis of driver eye-gaze dispersion during automation and in the transition, to assess the effect of the OoTL manipulations on visual attention allocation, comparing results to manual driving.

- **Chapter five** presents the analysis of driver eye-fixations to assess driver visual attention allocation before and during the transition and finds a different pattern of visual attention distribution for drivers who crash compared to those who do not.

- **Chapter six** reports on an analysis of drivers' perceptual-motor performance during critical events in automated driving and finds that drivers respond to the kinematic urgency of the scenario.

- **Chapter seven** summarises and discusses the work presented in this thesis, and provides some questions and directions for further work.

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CHAPTER 2

ENGAGING WITH HIGHLY AUTOMATED DRIVING: TO BE OR NOT TO BE IN THE LOOP?

ABSTRACT This desktop driving simulator study investigated the effect of engagement in a reading task during vehicle automation on drivers' ability to resume manual control and successfully avoid an impending collision. To avoid collision with the stationary vehicle, drivers were required to regain control of the automated vehicle and change lane. The decision-making element of this lane change was manipulated by asking drivers to move into the lane they saw fit (left or right) or to use the colour of the stationary vehicle as a rule (blue - left, red - right). Drivers' reaction to the stationary vehicle in manual control was compared to two automation conditions: (i) when drivers were engaged and observing the road during automation, and (ii) when they were reading a piece of text on an iPad during automation. Overall, findings suggest that drivers experiencing automation were slower to identify the potential collision scenario, but once identified the collision was evaded more erratically and at a faster pace than when drivers were in manual control of the vehicle. Short (1-minute) periods of automation used in this study did not appear to impede drivers' ability to complete simple operational and tactical-level driving tasks, following a system initiated take-over request. Results suggest that until there is an effective strategy to help drivers regain SA during resumption of control from Highly Automated Driving, they should be encouraged to remain in the driving loop.

2.1 Introduction

The promise of 'driverless vehicles' is slowly being realised, with testing under way by a number of major manufactures who have committed to bringing the first generation of such systems to market by 2020 (Merat et al., 2014). Current Advanced Driver Assistance Systems (ADAS), such as Adaptive Cruise Control (ACC), still require the driver to be in the control loop. These Level 1, function-specific automation systems (see SAE, 2014), are evolving into Level 2, combined-function automation and on to more intelligent Level 3, limited self-driving automation, or Highly Automated Driving (HAD), which will see necessary driver intervention only in certain situations that cannot be managed by the system. The concern from a human factors perspective is that this limited driver-state interaction may take drivers out-of-the-loop (OoTL), which Endsley and Kiris (1996) argue is a state induced by limited human-system interaction, causing an operator to lose awareness of the system state. The deleterious performance effects of the OoTL state have led some from cognate disciplines (Parasuraman and Riley, 2007) to suggest that HAD should be designed such that drivers are kept engaged and in the-loop for best performance and able to resume control of automation when system limitations are reached (Merat and Lee, 2012; de Waard et al., 1999), while others have argued that drivers should not be expected to continuously monitor the road (Jacoby and Schuster, 1997).

These opposing views may be due in part to the lack of a clear definition of what constitutes an OoTL state. Also, it is not currently clear what the 'loop' refers to, an information processing control loop (attentive to the driving task) or a sensory-motor control loop (vehicle control), or both. Previous investigations into drivers' ability to respond to Level 2 automation failures have explored the effects of workload and situation awareness (Jamson et al., 2013; Merat et al., 2012) and time budgets for resuming control (Gold and Bengler, 2014; Damböck et al., 2012), but none have compared the above distinction, or considered possible effects of different degrees of driver engagement with the driving task during HAD. It is important to have a sound theoretical basis for the OoTL concept, as it is frequently referred to in studies on HAD to explain drivers' ability to safely resume control from automation.

Another concern is the impact of scenario difficulty on drivers' return-to-manual performance, following system disengagement. With a few exceptions (e.g. Kircher, Larsson and Hultgren, 2013), studies have tended to examine take-overs for scenarios requiring operational-level responses, which are driving tasks that only require immediate longitudinal and lateral control by the driver (see Michon's levels of driving tasks, Michon, 1985). Given that the system limits which enforce a manual take-over are likely to be derived from more difficult scenarios than just those at an operational-level (e.g. road works, exiting a busy motor way), it is relevant to examine how drivers respond to higher, more tactical-level scenarios, which involve an element of rule-based decision making processing. However, there is only a very limited understanding of drivers' behavioural response to these levels in the context of HAD. The objective of this study was therefore to investigate the effect of varying degrees of engagement with the driving task, on behavioural responses to a potential collision scenario, introducing rule-based scenarios of varying workload to assess whether there were any behavioural differences between operational and tactical-level driving tasks. As a result, two hypotheses are evaluated: (a) the further drivers are disengaged from the driving task the worse their ability to respond appropriately to a potential collision scenario; (b) the greater the workload imposed on the driver during automation disengagement the worse their ability to resume control.

2.2 Methodology

2.2.1 Participants

Following approval from the University of Leeds Research Ethics Committee, 16 participants (8 male) between the ages of 19 and 26 (M = 21, SD = 1.54) were recruited via the driving simulator database and were paid £10 for taking part. No other particular criteria were used for recruiting participants, but they were required to have had a driving licence for at least one year and drive at least 500 miles per year.

2.2.2 Apparatus

This study was performed using the University of Leeds portable simulator (Figure 2.1, which was operated on a HP Z400 workstation running Windows 7, using custom made software. The visual simulation imagery was displayed on a Samsung 40" wide-screen 1920x1080 monitor, rendered at 60 Hz. Vehicle control inputs were via a Logitech G27 dual-motor force feedback steering wheel and pedals.

During manual driving, participants were entirely responsible for the manipulation of standard longitudinal (accelerator and brake pedals) and lateral (steering wheel)

Figure 2.1: Driving simulator set-up. Central display unit (inset) indicated automation status. A 'beep' tone alerted drivers when automation was turned on/off.

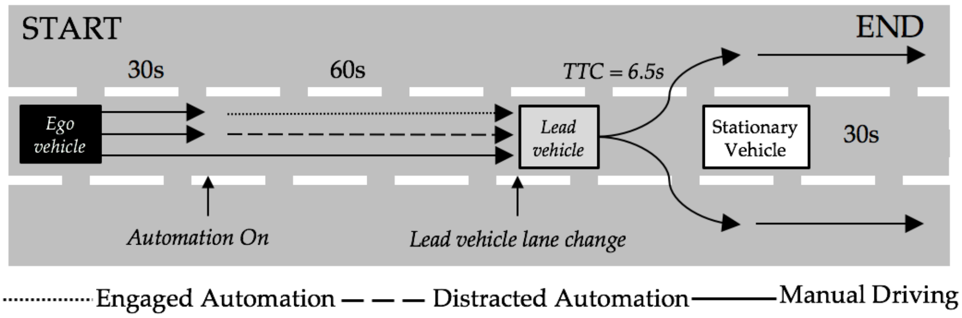

Figure 2.2: Schematic representation of the driving scenario.

controls. During HAD, the longitudinal controller was effectively an ACC with a default target speed of 67mph (108 km/h) with target headway fixed at 1.5 seconds, which could not be adjusted by the driver. The lateral controller resembled a Lane Keeping System (LKS) and, on activation, attempted to maintain the vehicle in the centre of the current lane occupied. HAD was activated and deactivated automatically by the simulation. Drivers were notified of changes to automation state with a non-intrusive 'beep' tone.

2.2.3 Design and Procedure

A within-subjects 3x3 repeated-measures design was used, with all participants completing all conditions. The independent variables were Drive (manual, engaged automated, distracted automated) and Load (no rule, congruent rule, incongruent rule).

Upon arrival, participants were briefed on the requirements of the study and their ethical rights. After completion of informed consent, participants were given the opportunity to practice manual driving and HAD within a free-flowing 3-lane motorway. Drivers were asked to ensure safe operation of the vehicle, including timely take-over from HAD, if necessary.

In the experimental session, drivers initiated a trial by depressing the accelerator pedal. All trials began in manual driving behind a lead vehicle travelling in the middle lane at 67mph (108km/h). As shown in Figure 2.2, after 30 seconds of manual driving, one of three 60 second conditions was presented in a counter-balanced order: In the manual condition, drivers had full manual control of the vehicle. This corresponded to an Active & In-the-loop state. In the engaged automation condition, participants observed the driving scene but took their hands away from the steering wheel and foot off the accelerator pedal while the automation was active. This aligned with a Passive & In-the-loop state. In the distracted automation condition, drivers were asked to read aloud a selection of text that was displayed on an iPad located to the bottom left of the steering wheel (Figure 2.1). This trial was designed to induce a Passive & Out-of-the-loop state.

After this 60 second period, the lead vehicle changed lane (to the right or left) to reveal a stationary vehicle obstructing the middle lane. Participants were instructed to change lane to avoid colliding with this stranded vehicle. When automation was activated, this manoeuvre of the lead vehicle coincided with the deactivation of automation. Four 'ghost' trials were also randomly assigned during the experiment, where a stranded vehicle did not exist in the middle lane.

To induce different loads after the lead vehicle changed lanes, drivers' lane changing manoeuvre was governed by one of three rules. In the no rule condition, participants were free to choose the direction of travel to avoid collision with the stranded vehicle. This only entailed a control element and was therefore considered

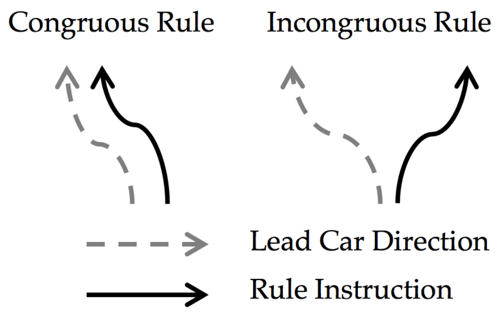

Figure 2.3: Representation of the congruous and incongruous rule conditions.

an operational-level driving task. In the congruous and incongruous rule conditions, participants were required to change lane in a particular direction, depending on the colour of the stationary vehicle (green = left, red = right). These were therefore considered to be tactical-level driving tasks. In the congruous rule condition, the direction in which the lead vehicle changed lane was the same as the direction instructed by the rule, while in the incongruous rule condition the opposite was true (Figure 2.3). After passing the stranded vehicle, manual driving continued for a further 30 seconds, after which the driving scene faded out and the trial was over. The next trial then began as soon as drivers depressed the accelerator pedal. All participants completed the trials involving the no rule condition first, followed by those involving the two rule conditions. This was to ensure that the rules for the congruous and incongruous rule conditions did not confuse participants during the no rule condition. Based on estimations of future sensor ranges, and results from previous studies (Gold and Bengler, 2014; Damböck et al., 2012) the Time To Collision (TTC) between the stationary vehicle and the simulator vehicle was 6.5 seconds. In order to control for TTC in manual driving, drivers were required to maintain a set headway of 42m, using chevron markings on the roadway as a guide. Participants completed 18 trials in total and the time taken to complete the experiment was around 1.5 hours.

A number of dependent variables were used to study performance; maximum lateral and longitudinal acceleration, time to first steer and time to lane change. A distribution of how drivers reacted to avoid the collision: steering, braking, steering and braking, was also noted. Measures of maximum lateral and longitudinal acceleration were taken from when the stationary vehicle was revealed, until the end of the trial, and were used as indicators of stability of control. Time to first steer considered the time from when the stationary vehicle was revealed, until the first steering input greater than 2° was applied. Time to lane change refers to the time from when the stationary vehicle was revealed until all four corners of a driver's vehicle were in an adjacent lane.

2.3 Results and Discussion

A 3x3 repeated measures Analysis of Variance (ANOVA) was conducted on maximum lateral and longitudinal acceleration comparing the values in the three Drives (manual, engaged automation, and distracted automation) and at the three Load levels (no rule, congruous rule and incongruous rule). Results showed a significant main effect of Drive on maximum lateral acceleration [$F(2,14) = 15.71$, $P<.001$, $\eta_p^2 = .51$; Figure 2.4] and post-hoc Bonferroni tests showed higher maximum lateral accelerations for both engaged automation and distracted automation drives, compared to the manual drive ($p=.008$ and $p<.001$, respectively). Vehicle control, as revealed by lateral acceleration, was, therefore, more erratic the further drivers were out-of-the-loop. Comparison between automation drives was not significant. There were no main effects of maximum longitudinal acceleration and also no interaction effects.

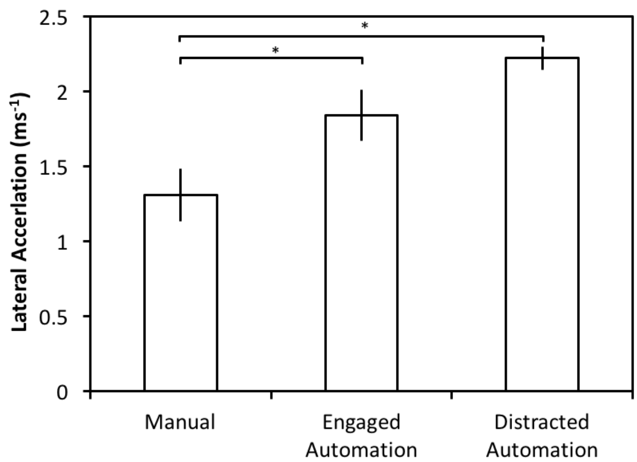

Figure 2.4: Maximum lateral acceleration for Drive (Error bars = SE, * = significant difference between conditions).

To observe how drivers responded to a potential collision, time to first steer and time to lane change were subjected to a 3x3 ANOVA, with the same factors as above. There was a significant effect of Drive on time to first steer [$F(2,14) = 9.98$, $p=.001$, $\eta_p^2 = .39$; Figure 2.5] with post-hoc Bonferroni tests showing that, compared to manual

Table 2.1: Brake and Steer combinations for Drive.

	Manual	Engaged Automation	Distracted Automation
Steer Only	72.9 %	81.25 %	70.8 %
Steer and Brake	27.1 %	18.75 %	29.2 %

driving, drivers took significantly longer to generate their first steering manoeuvre during both engaged automation (p=.002) and distracted automation (p=.037). There was no significant effect of Load and there was also no interaction effect present between Drive and Load on time to first steer.

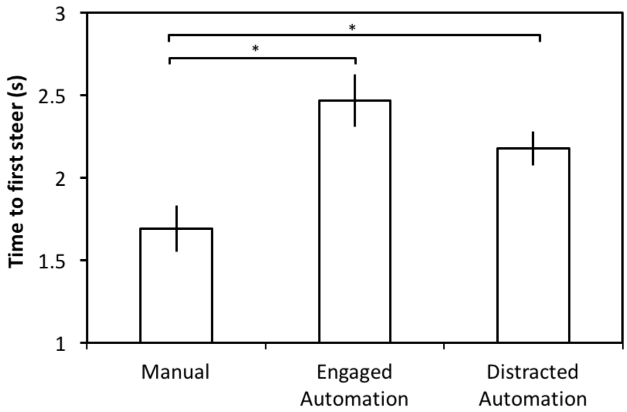

Figure 2.5: Time to first steer for Drive (Error bars = SE, * = significant difference between conditions).

The effect of Drive on time to lane change approached significance [F(2,14) =3.60, p=.058, η_p^2= .19; Figure 2.6]. There was no significant effect of Load on time to lane change was no interaction between Drive and Load. Taken together, these results suggest that, regardless of whether they were distracted or not, automation delayed drivers' first steering input. However, when observing the scene during automation, drivers' response to the collision seems to have been more calculated and more under their control, taking time to steer to the adjacent lane, with less lateral acceleration. When engaged in the reading task, drivers seem to have simply responded to the beep denoting the disengagement of automation, changing lane quickly and more erratically, as indicated by their maximum lateral deviation.

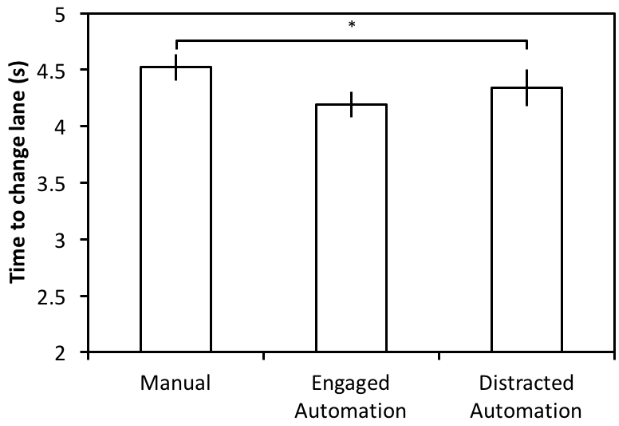

Figure 2.6: Time to lane change for Drive (Error bars = SE, * = significant difference between conditions).

This difference in tactic between engaged and distracted automation is also shown in the steering and braking behaviour (Table 2.1), where similar results were seen between engaged automation and manual driving, different to that of distracted automation. Whilst in 70.8% and 72.9% of cases in the manual and distracted automation drives participants avoided the obstacle by only steering into the next lane, for engaged automation the proportion of cases where participants steered increased to 81.28%. Chi square tests revealed that these differences were not significant, however. There were no collisions with the stationary vehicle across all trials. In terms of decision-making behaviour based on the condition rules, for the no rule condition, in 95.83% of cases drivers chose to follow the lead vehicle to avoid a collision, in line with similar findings by Malaterre et al. (1988). Drivers managed to adhere to the rule in 100% and 98% of cases for the congruent and incongruent rule conditions, respectively.

2.4 Conclusions

There has been a great deal of interest regarding how to safely re-engage drivers in manual driving following a period of HAD (Merat et al., 2014), with the out-of-the-loop phenomenon cited as a primary contributor to impaired performance. The main objective of the current study was to investigate the behavioural differences that might exist between different levels of engagement with a driving task, and whether and to what extent these interact with operational and tactical-level driving tasks (Michon, 1985).

Apart from drivers braking less often in the engaged automation than in distracted automation and manual conditions, which showed similar response profiles, our results showed that there was no difference between the manual and engaged automation conditions, across all variables. Though, since the trials were rather stereotypical, it is likely that, with repeated exposure, drivers increasingly learned how to deal with the critical events. However, as found in previous studies (Merat et al., 2012), compared to manual driving, drivers' response was significantly slower following brief 1-minute periods of automated driving, even during engaged automation, where drivers were focused on the road scene immediately prior to the critical event. In addition, automation seems also to have impacted on the speed and quality of lane changes, with lane changes completed at a faster rate once initiated, and also with significantly higher maximal lateral accelerations for both automation conditions, compared to manual. This demonstrates that the key factor affecting the response is whether the driver is actively engaged in vehicle control (i.e., an active part of the sensory-motor control loop).

The OoTL concept seems, therefore, to encompass a strong element of physical control, with the effects of cognitive control possibly a more subtle addition. Certainly, the possible priming of the repeated-measures design suggests that any observed effects of being out of the cognitive control loop are conservative and, therefore, deserve more focused investigation. To assist in this, future studies on HAD making reference to the OoTL phenomenon should attempt to distinguish which loop is being addressed. Our results show that what is most important is whether the driver is in vehicle control and that this aspect should form the basis for any strategies to re-engage the driver in manual control. Nevertheless, humans are poor supervisors (Parasuraman and Riley, 2007) and therefore aspects of information processing control in HAD needs to be scrutinised by further studies to establish whether the observed behaviour is valid for more difficult scenarios, under shorter TTCs and after longer periods of HAD. Finally, in the same way that steering entropy has benefited our understanding of driver distraction, there is a pressing need to develop an objective measure of the quality and safety of a take-over, rather than relying on a series of reaction times, which would fall short of capturing the difficulty inherent in more strategic-level driving tasks.

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CHAPTER 3

DRIVER INATTENTION AND VEHICLE AUTOMATION: HOW DOES ENGAGEMENT AFFECT RESUMPTION OF CONTROL?

ABSTRACT This driving simulator study, conducted as part of the EC-funded AdaptIVe project, investigated the effect of level of distraction during automation (Level 2 SAE) on drivers' ability to assess automation uncertainty and react to a potential collision scenario. Drivers' attention to the road was varied during automation in one of two driving screen manipulation conditions: occlusion by light fog and occlusion by heavy fog. Vehicle-based measures, drivers' eye movements and response profiles to events after an automation uncertainty period were measured during a highly automated drive containing one of these manipulations, and compared to manual driving. In two of seven uncertainty events, a lead vehicle braked, causing a critical situation. Drivers' reactions to these critical events were compared in a between-subjects design, where the driving scene was manipulated for 1.5 minutes. Results showed that, during automation, drivers' response profile to a potential collision scenario was less controlled and more aggressive immediately after the transition, compared to when they were in manual control. With respect to screen manipulation in particular, drivers in the heavy fog condition collided with the lead vehicle more often and also had a lower minimum headway compared to those in the light fog condition.

3.1 Introduction

The emergence of vehicle automation presents a radical shift in the way that drivers interact with their vehicles and the driving task itself. Extensive research has been carried out on the human factors issues relating to lower levels (SAE Level 1 and 2) of vehicle automation (such as Adaptive Cruise Control (ACC); for a review see De Winter et al. 2014). However, investigating the human factors implications of higher levels of automation up to SAE Level 5 have been somewhat constrained by the fact that the development and implementation of this technology are still some way off. It is argued that as automation advances, it will increasingly relieve drivers of the moment-to-moment demands of driving (Lee, 2013). However, as these systems will likely be fallible for some time to come the driver will, on occasions, be required to intervene and resume control from automation.

Understanding the factors that influence driver distraction is underpinned by a strong theoretical orientation with multiple definitions. Amongst these, Lee et al.'s (2008, p. 38) is widely used: "*Driver distraction is a diversion of attention away from activities critical for safe driving towards a competing activity*." A key assumption here is the competition for attentional resources between the driving task and another - secondary - activity. For the early generations of automation (Level 1-3; SAE, 2014), however, the "activities critical for safe driving" will be some combination of the driver monitoring the environment and being the fall-back operator. However, increasing automation is likely to encourage driver engagement in secondary tasks, because drivers are no longer required to participate in the driving task at all times (Merat and Lee, 2012). Indeed, previous work conducted in our laboratories has found that during Highly Automated Driving (HAD), drivers are more likely to engage in tasks unrelated to driving (Carsten et al., 2012). The nature of this distraction during automation can be both driver-initiated and stimulus-oriented, whilst drivers are also susceptible to stimulus-independent thought or mind-wandering. Such shifts in attention can interfere with processing of or reaction to safety-critical events and stimuli, such as roadway hazards (Li et al., 2012). As the level of vehicle automation increases, drivers are likely to further disengage from driving and may, for example, fail to recognise and act upon a hazard when faced with a take-over-request (TOR, Gold et al., 2013).

Therefore, less effective driving performance during the transition is likely unless drivers are given the correct information for resumption of control in an appropriate and timely manner. For example, drivers' reaction time to critical events can be markedly reduced during distraction with a secondary task (Merat et al., 2012). Driver distraction research has traditionally employed a dual-task paradigm to explain performance via competition for attentional resources where driving is the primary task (Strayer and Johnston, 2001). During automation, however, the driver is not in control of the vehicle, which means that a dual-task paradigm is not possible in the study of transitions. Therefore, to study the effects of stimulus-independent thought that may occur before, during and/or after a transition, there is need for the development of a suitable methodology to establish what mechanisms contribute to how a driver might go from being engaged with the driving task during automation to being disengaged, or prone to mind-wandering, a process also referred to as passive fatigue (see Neubauer, Langheim, Matthews and Saxby, 2011). It is also important to establish whether and how the effect of such states can be easily measured.

Many of the studies on transitions have rather loosely attributed less effective driving after return-to-manual control to phenomena such as out-of-the-loop (OoTL) or having lost situation awareness (SA). Unhelpfully, however, there is some confusion around the distinction between the OoTL state and SA in terms of what the two concepts encompass; for example, whether they engage specific attentional domains or whether they are somewhat analogous. From a purely theoretical perspective, Endsley (1995) suggests a loss of SA is related to elements within the environment while being OoTL is specifically linked to elements of the automation status itself. To further complicate the matter, there is some debate around the usefulness or validity of each concept (Carsten and Vanderhaegen, 2015). One could draw a distinction between attentional aspects and physical aspects of control. For example, in a recent driving simulator study, we attempted to isolate the effects of the attentional and physical aspects of driving on a driver's ability to resume manual control and respond to an impending collision scenario after 60 s of automation (Louw, Merat, and Jamson, 2015). In the first automation condition, participants were asked to keep their eyes on the road, while in the second they were distracted by a secondary task (reading on a PDA, which forced their visual attention away from the driving scene).

To assess the physical aspect of resuming control, we compared driver responses in both automation conditions to a manual condition. Our results showed that simply having to regain physical control is an important factor in these contexts, but the extent to which cognitive disengagement alone influences performance is yet to be established. It seems, therefore, that the difference between a driver who has lost SA and a driver who is OoTL is that the latter state also accounts for the effect of not being in physical control of performance. In addition, the definition of the OoTL concept is more descriptive about how the loss of SA arises. Endsley (1995) argues that the passive monitoring of automation, as a result of not being in physical control, leads to decreased vigilance and a lower understanding, which leads to a loss of SA. Our proposed schematic representation of the OoTL phenomenon, shown in Figure 3.1, suggests that the loss of physical control and the loss of SA can arise independently as a result of vehicle automation and can lead to less effective return-to-manual performance. Importantly, the loss of physical control can also act on SA, which can result in less effective performance.

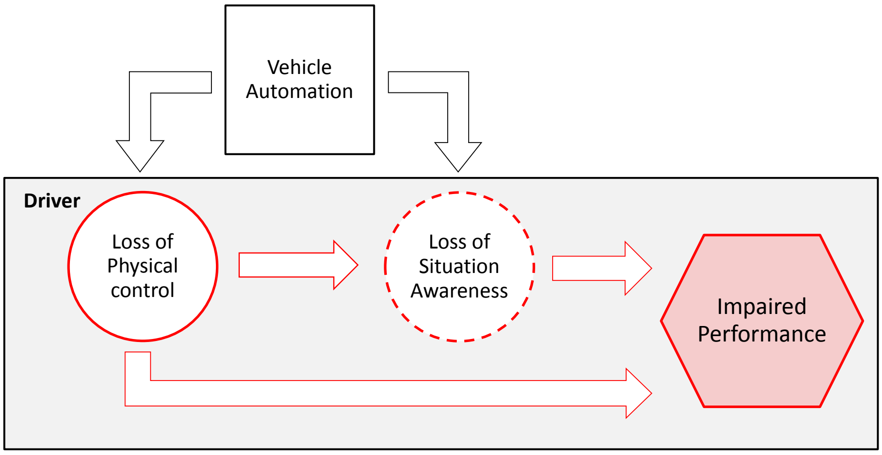

Figure 3.1: Schematic representation of the out-of-the-loop (OoTL) phenomenon

Based on studies of OoTL problems in human-automation-interaction in cognate domains, such as aviation (Molloy and Parasuraman, 1996), it can be argued that the further drivers are removed from the driving loop, the worse their return-to-manual performance. This stresses the need to investigate the effect of automation as a distraction, and in particular how stimulus-independent thought brought about by automation affects drivers resumption of manual control. However, while investigating the effects of stimulus-oriented thought simply requires engagement in a secondary task, inducing stimulus-independent thought is more challenging. Therefore, the main aim of this study was to develop a means of simulating various degrees of the driver OoTL states during HAD. To do this, we worked back from Endsley's (1995) definition of SA and OoTL state. We argued that simply adding lateral and longitudinal assistance (Level2/3 automation) induced the physical aspect of being OoTL. To induce loss of SA, we progressively limited the driver's ability to perceive information about the status of the automated system and the driving environment itself, by overlaying a fog-like occlusion screen onto the driving scene. We reasoned that, by partially blocking the road scene (light fog, see below), drivers would be somewhat aware of their surroundings, whilst blocking the road scene completely (heavy fog) would completely remove drivers' awareness of their surroundings.

With a few notable exceptions (e.g. Beller et al., 2014), most previous studies on transitions (e.g. Gold and Bengler, 2014; Hergeth et al., 2015) have investigated responses to take-over-requests (TOR) brought on by an automation system's failure or limitation. These studies have mostly incorporated mandatory transitions (Goodrich and Boer, 1999) or TORs, which effectively instruct the driver to resume control. It is likely, therefore, that such methods simply assess drivers' ability to react to an alarm or take over message. Although investigating how drivers perform when they take back control is an important consideration, the ability to process information and make decisions in the face of an automated system with limited capabilities is also valuable. Therefore, in this study, we used the concept of automation uncertainty (or system limitation) not only to improve understanding of the driver-automation-interaction, but also as a means of assessing whether drivers could recognise the unfolding of a potentially critical event (which is an important element of SA). We argue that the more drivers were taken OoTL, the worse their ability to recognise and respond to road-related hazards.

While the driver's role in monitoring the system varies according to the level of automation, the driver is largely removed from vehicle control when automation increases beyond SAE level 2 (SAE, 2014). Jamson et al. (2013) suggest that this then limits the usefulness of many of the metrics traditionally used to assess driver behaviour, such as Standard Deviation of Lateral Position (SDLP). There is, therefore, a need to develop a set of objective, formative measures of the quality and safety implications of the transition (Louw et al., 2015), rather than relying on system-dependant evaluative measures. Therefore, another aim of this study was to consider alternative measures to assess the transition to manual control from automation.

3.2 Methods

3.2.1 Participants

Following approval from the University of Leeds Research Ethics Committee, 30 participants (20 male) between the ages of 22 and 69 (M=39.2, SD=14.45) were recruited via the driving simulator database and were paid £20 for taking part. Participants had normal or corrected-to-normal vision, were required to have had a driving licence for at least five years (M=20.17 SD=15.26) and drive at least twice a week (mean annual mileage was 8,616 miles).

3.2.2 Design and Procedure

Materials

The experiment was conducted in the University of Leeds Driving Simulator, which consists of a Jaguar S-type cab with all driver controls operational. The vehicle is housed within a 4m spherical projection dome and has a 300° field-of-view projection system. A v4.5 Seeing Machines faceLAB eye-tracker was used to record eye movements at 60Hz.

Design

A repeated measures mixed design was used for this study, with a between-participant factor of Condition (no fog, light fog, heavy fog, heavy fog + task) and within-participant factors of Drive (manual, automated) and Event (critical event 1, critical event 2).

The experimental session consisted of two drives (manual and automated) lasting about 20 minutes each, and to alleviate symptoms of fatigue, participants were given a short break between drives. Participants drove exactly the same road in both drives, but a screen manipulation was applied to the automated drive only. The order of drives was counterbalanced across participants, with half of the participants performing the manual drive first and the automated drive second, or vice versa. As shown in Figure 3.2, within each drive there were seven discrete events, each lasting approximately

150s. Events 1,3,4,5 and 7 were non-critical while events 2 and 6 were critical. During the non-critical events, the lead vehicle would either speed up or change lane while in the critical events the lead vehicle would brake, resulting in an impending collision scenario (2,6). The time-to-collision (TTC) at the point of the lead vehicle braking was 5s.

To induce the OoTL state during the automated drives we employed two screen manipulation techniques. In the light fog condition, a translucent grey filter was overlaid onto the road scene. Here, drivers were able to distinguish elements of the road environment and movements of the surrounding vehicles, the aim of the manipulation was to simulate a process whereby limited visual attention was directed towards the screen, for example when drivers are engaged in reading an email but partly aware of the driving scene in their peripheral vision. In the heavy fog condition, an opaque grey filter overlaid the road scene. This manipulation effectively blocked all visual information from the road environment. For both manipulations, drivers were also unable to see the HMI which portrayed the status of the automated system.

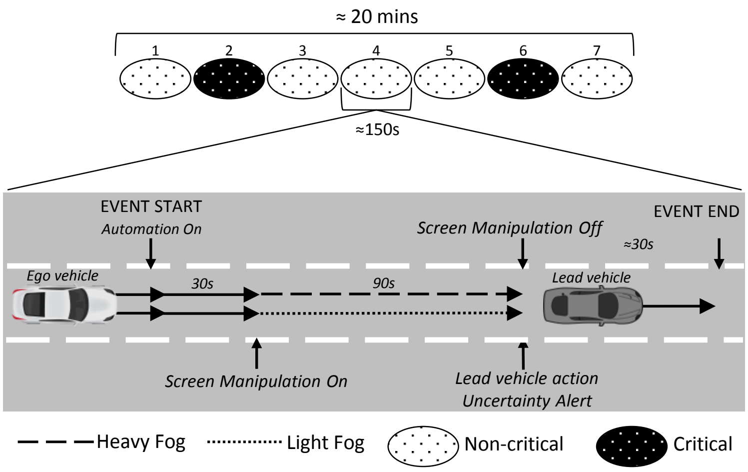

Figure 3.2: Schematic representation of each discrete event, with events two and six shown as critical.

Procedure

Upon arrival, participants were briefed on the description of the study and were asked to sign a consent form, with an opportunity to ask any questions, if required. They were then given the opportunity to practice manual driving and Highly Automated Driving (HAD) within a free-flowing 3-lane motorway. During the practice session, participants were talked through the various aspects of the vehicle HMI (Figure 3.3) were shown how to engage and disengage the automation, and were also shown the screen manipulation they would encounter during the experimental automated drive. The road contained ambient traffic, but participants did not experience the critical events during the practice drives.

Figure 3.3: Example of the in-vehicle HMI with the FCW symbol on the left and the Automation Status Symbol on the right.

In terms of automation uncertainty, participants were told that, should the automation become uncertain during the drive (see below for how this was portrayed), they should monitor the driving environment and determine for themselves whether or not to intervene. Participants were instructed to drive in lane 2 of the motorway for the duration of the drive but were permitted to change lane in critical situations, and were told to move back into lane 2 as soon as possible. Drivers were asked to obey the normal rules of the road and to ensure safe operation of the vehicle.

To engage the highly automated driving system, participants pressed a button on the steering wheel. To disengage automation, participants would either press the same button, turn the steering wheel more than 2° or press the brake pedal. During the automated drive, participants were asked to move to the centre of the middle lane as soon as convenient and then activate automated driving as soon as it was available (see Figure 3.2) which typically occurred 30 s after the drive began. If drivers did not engage automation, after 60 s the system engaged automatically. The activation of automation constituted the start of an event. After 30 s of automated driving, one of two 90 s screen manipulations began. It is important to note that the vehicle dynamics, as well as all auditory cues, remained active during the screen manipulations. To ensure drivers were able to disengage from the driving task during automation without experiencing a high level of fatigue, we chose a screen manipulation duration of 90 s. After each screen manipulation, the presence of a lead vehicle triggered an uncertainty scenario. At this point, the screen manipulation concluded, the driving scene was again visible, and simultaneously the automation status changed from "Engaged" to "Uncertain". Drivers were notified of this change by an auditory 'beep' and the automation status symbol, which was now visible, changed from green to flashing yellow. The driver was then expected to monitor the situation and intervene if necessary. After 3 s, the lead vehicle would make one of three manoeuvres: In the non-critical event (1,3,4,6) the lead vehicle either moved out of lane 2 or sped up, while in the critical events (2,6) the lead vehicle braked sharply with a maximum deceleration of 5.0 m/s^2.

Human-Machine Interface (HMI)

The status of the vehicle's automated system was indicated by the colour of a steering wheel symbol that was located on the left panel of the central display unit (See Figure 3.3). There were four possible combinations of this status, as outlined in Table 3.1. Any change to the automation state, whether driver- or system-initiated, was accompanied by a non-intrusive 'beep' tone.

In addition to the automation status, a Forward Collision Warning (FCW) symbol was included in the left panel of the central display unit Figure (3.3). Active only when automation was engaged, this system provided a visual approximation of the headway of the lead vehicle in seconds. A continuous alarm alerted drivers of an imminent collision whenever TTC with the lead vehicle was below a threshold of 2 s. To further deprive drivers of system information during automation, the automation status (steering wheel) and the FCW status were also hidden. However, participants were able to reveal the HMI at any point by pulling the left indicator stick towards them. This action illuminated the HMI for 2 s. Participants were able to do this as often as they wanted.

Table 3.1: Description of the automation status HMI.

Steering Wheel Colour	**Automation status**	**Description**
Grey	Unavailable	Indicates that automation is not available to be engaged by the driver. Appears during the first 30 s of the automated drive and when the vehicle is not in the middle of the middle lane.
Flashing green	Available	Indicates that the driver is able to engage automation. Appears when the vehicle is in the middle of the middle lane.
Green	Engaged	Indicates that the vehicle is being controlled by the automated system, which manages gentle manoeuvres and is not designed to respond to critical and unexpected incidents.
Flashing yellow	Uncertain	Indicates that the automated system, while currently functioning normally, thinks that in the near future there may be a situation on the road that it cannot deal with and, therefore, requires the driver to monitor the road and intervene where necessary.
Red	Disengaged	Indicates that the automation is temporarily unavailable. Appears immediately after automation is disengaged.

3.3 Results and Discussion

In this experiment, we attempted to simulate the feeling of being OoTL during HAD by limiting system and environmental information, and examined drivers' assessment of the criticality of automation uncertainty warnings and their ability to respond to critical situations. We hypothesised that as drivers are further removed from the loop their ability to assess and respond to critical situations would be degraded. Additionally, we expected that drivers' ability to recognise and respond to these critical situations would be worse in automation, compared to manual driving and that response in heavy fog conditions would be worse than light fog, which has some visibility of the driving environment.

3.3.1 Validating the OoTL state

To assess the validity of the screen manipulation technique for inducing a state of being OOTL, we considered drivers' visual attention to the road scene and driving task by observing its distribution across five spatial regions as illustrated in Figure 3.4, similar to a technique used by Hughes and Cole (1988) and Carsten et al. (2012). We used Percentage Road Centre (PRC; Victor, 2005) all seven events, and during both manual and automated driving. PRC was defined as the mode of gaze fixations that fell within the road centre area, a 6° circular region within a 60 s moving window. As described in Carsten et al. (2012), the left region covered fixations to the centre console (e.g., radio controls) as well as the left side mirror, door window, and passing traffic in the adjacent lane. The right region covered the right side mirror, door window, and passing traffic in the adjacent lane. The bottom region covered mainly the dashboard, where the speedometer, automation HMI, and a variety of gauges were located. The top region covered mainly the sky. We reasoned that automation would reduce drivers' attention to the road and, therefore, reduce PRC values in the central region, in particular.

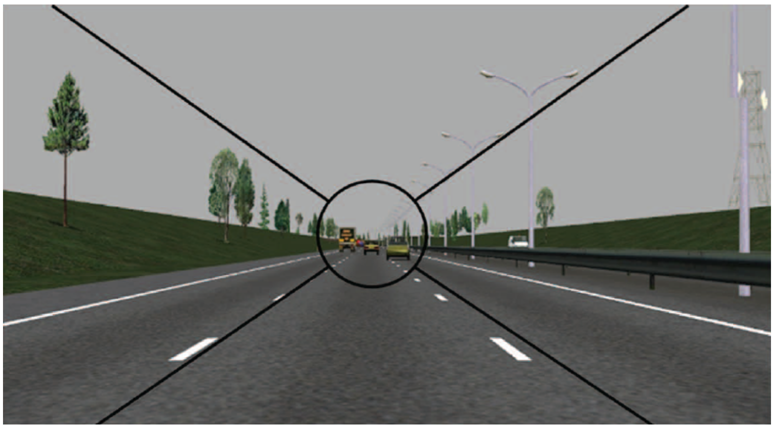

Figure 3.4: Visual attention regions (Carsten et al., 2012).

To understand what information may be useful to drivers when they are required to re-engage in the driving task, we also calculated the point of first gaze fixation after each screen manipulation ended in the two automation conditions. Finally, we counted the frequency of occasions drivers used the indicator stick to glimpse at the HMI, in order to understand whether and to what extent drivers were engaging with the driving task during the periods of screen manipulation when automation was on.

3.3.2 Distribution of visual attention

The drivers' gaze behaviour was analysed across Screen Manipulation conditions. PRC during periods of Screen Manipulation for all seven periods of automation was compared using a one-way Analysis of Variance (ANOVA), with Drive (*automation, manual*) as a within-subjects factor. Figure 3.5 shows that when compared to those in the heavy fog condition, participants in the light fog condition, fixated on the road ahead (depicted by the Centre bar) significantly more often than any other visible sections of the driving environment (F(1,26) = 31.984, p<.001, η_p^2 = .417). These can be compared to the central PRC values in the manual drive, which were 73.77% for the light fog group and 73.50% for the heavy fog group. By the same token, for the same period, less fixations were observed towards the bottom of the screen (including the dashboard area) (F(1,26) = 4.792, p=.001, η_p^2= .363) and the left and right of the screen (including the side mirrors) (F(1,26) = 4.480, p=.044, η_p^2= .147).

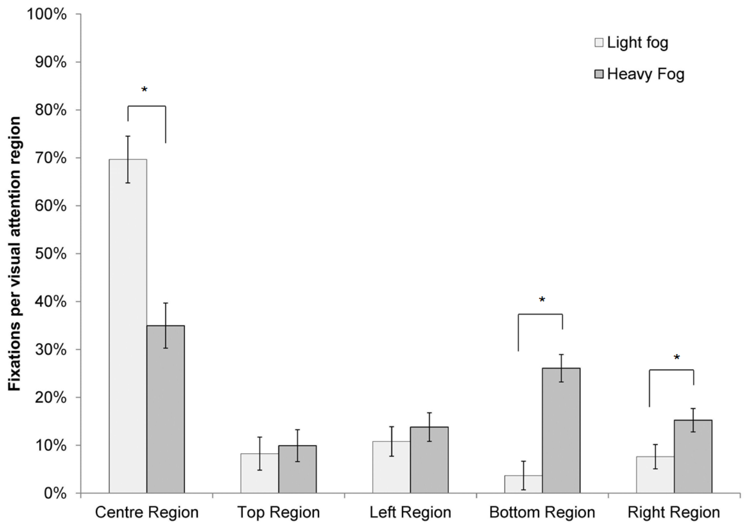

Figure 3.5: Percentage Road Centre during Light Fog and Heavy Fog automation drives. Error bars = SEM. * indicates significant difference.

3.3.3 Engagement with the system

Data were analysed using a mixed-design ANOVA with a within-subjects factor of Events (7) and a between-subject factor of Condition $(lightfog, heavyfog)$. Mauchly's test indicated that the assumption of sphericity had been violated $(\chi^2(20) = 151.86, p < .001)$, and therefore degrees of freedom were corrected using Greenhouse-Geisser estimates of sphericity (ϵ =0.26). There was a main effect of Events [F(1.557, 42.027) = 5.185, p=.015, η_p^2.161], where drivers glimpsed at the automation status less often as the drive progressed over the seven events (Figure 3.6). This suggests that, over time, participants were more disengaged from the driving task, possibly either because they trusted the system more or because the system status was always the same when they checked. There was no main effect of Condition, however, which indicates that drivers' engagement was not influenced by whether or not they could see what was happening in the road environment during light fog versus heavy fog conditions. There were also no significant interactions between Condition and Event.

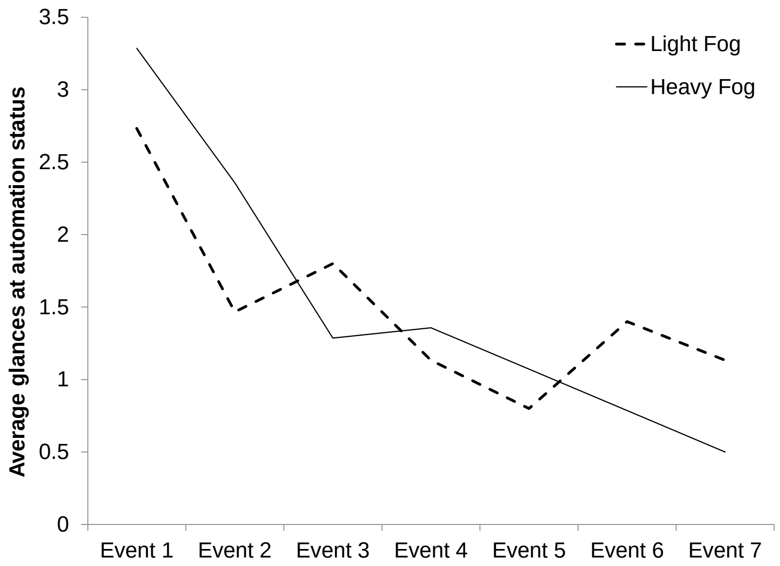

Figure 3.6: Average number of 'peeks' at the hidden automation status throughout the light fog and heavy fog automated drives.

3.3.4 First gaze fixation

When the screen manipulation was turned off, more of the participants driving in the light fog condition looked at the road centre first (M=76.53% vs. M=66.67%) compared to the central display area, which contained the dashboard (M=8.16% vs. M=15.24%). However, a chi-squared test indicated that these differences were not statistically significant.

3.3.5 Driver response to critical events

Driver response measures during the critical events included automation disengagement time, a count of the process by which participants disengaged automation, as well as how many lane changes and collisions were experienced.

Automation disengagement time was analysed with a mixed-design ANOVA, with Event (*critical event 1*, *critical event 2*) as a within-subjects factor and Condition (*light*

Table 3.2: Disengagement methods for all cases in the critical and non-critical events.

	Critical Events (2,6)		Non-Critical Events (1,3,4,5)	
	Light Fog	Heavy Fog	Light Fog	Heavy Fog
Brake	18/30	23/30	2/60	8/60
Steer	9/30	7/30	9/60	6/60
Button	3/30	0/30	4/60	0/60
Automation Remained Engaged	0/30	0/30	45/60	46/60

fog, heavy fog) as a between-subjects factor. Chi-squared tests were conducted on lane change and collision counts.

There was no effect of Condition on automation disengagement time [F(1,27) = .991, p=.328, η^2_p= .034], suggesting that being OoTL prior to the critical event did not impede drivers' ability to react to the lead vehicle braking. There was also no effect of Event and no interactions between Event and Condition. However, as argued earlier, drivers' disengagement times might be considered less informative than whether and how they reacted. Results from Table 3.2 show that, for the non-critical events, in both the light fog and heavy fog conditions, automation was only disengaged in a quarter of cases, while for the critical events automation was disengaged in all 60 cases. Importantly, only 8 of these critical event disengagements occurred before the lead vehicle braked, suggesting that, during the automation uncertainty even drivers were able to regain sufficient SA to recognise the criticality of the situation (lead vehicle braking, reduced TTC and the likelihood of a collision). Drivers were not explicitly told how the system would behave in a critical situation, which suggests that when drivers do not know the limitations of their automated systems, they trust their own abilities over those of the system or they could be suspicious until they trust it.

To assess associations for lane changes, a chi-squared analysis was conducted. Table 3.3 shows that, drivers made fewer lane changes in the automation condition compared to manual. However, even though drivers were able to recognise the criticality of the event following automation, they were still unable to avoid a collision, with a chi-squared test revealing that significantly more collisions with the lead vehicle occurred in the automation than manual drives (p=.01). During automation, however, there was a marked increase in collisions when the heavy fog manipulation was on,

Table 3.3: Lane Changes and collision counts (in brackets).

	Automation		Manual	
	Critical Event 1	**Critical Event 2**	**Critical Event 1**	**Critical Event 2**
Light Fog	7 (2)	10 (1)	11 (1)	12 (0)
Heavy Fog	9 (7)	9 (3)	11 (2)	11 (1)

compared to the light fog condition, with the trend more prominent in the first critical event. These results suggest that, compared to manual driving, automation reduced drivers' ability to avoid a collision, and particularly so when drivers were further out of the loop in the heavy fog condition.

3.3.6 Vehicle measures

To examine driver's overall vehicle control during the transition in critical events (2,6), longitudinal driving performance was measured using maximum deceleration from the point of resumption of manual control to the end of the critical event, which was 10 seconds after the lead vehicle's brake light illuminated. Taken in the same time frame, lateral driving performance was measured using maximum lateral acceleration, which has also been used previously as a measure of vehicle control (Gold et al., 2014; Louw et al., 2015). Minimum distance headway was also calculated and was a measure of how close a driver came to the rear of the lead vehicle.

A mixed-design ANOVA was conducted on Drive (*automation, manual*) and Event (*critical event 1, critical event 2*) as within-subjects factors and Condition (*light fog, heavy fog*) as a between-subjects factor, for maximum lateral acceleration, maximum deceleration and minimum headway.

Maximum lateral acceleration

Maximum lateral acceleration was significantly higher in the automated drives, compared to the manual drives (M=1.99m/s^2; SE=0.19 m/s^2, vs. M=1.13 m/s^2; SE=0.12 m/s^2) [F(1,28) = 9.382, p=.005, η^2_p= .251), suggesting that following re-entry into manual control drivers displayed less stable vehicle control in response to a potential collision scenario, compared to manual driving. However, there was no effect of Condition or Event and also no interactions.

Maximum deceleration

There was also a significant effect of Drive on maximum deceleration [F(1,25)=13.774, p=.001, η_p^2=.355], with participants reducing their speed at a higher rate in the automated drive (M=-5.94 m/s^2; SE=0.45 m/s^2, vs. M=-4.25 m/s^2; SE=0.46 m/s^2). As shown in Figure 3.7, this effect was qualified by the interaction between Drive and Condition, [F(1,28)=9.382, p=.005, η_p^2=.251], where the difference in maximum deceleration between the automation and manual drives was significantly greater in the light fog condition. There was no effect of Condition or Event and no other interactions.

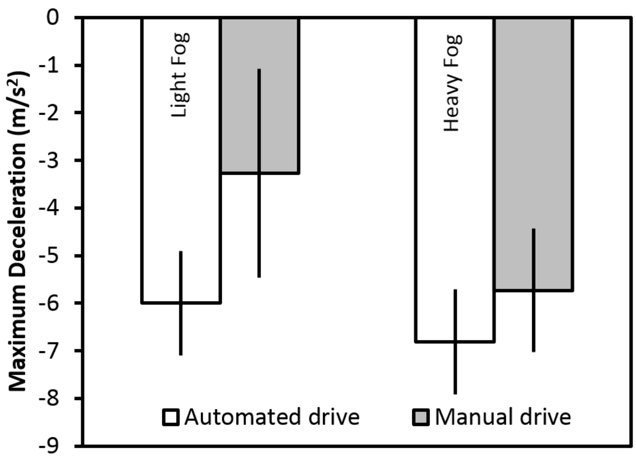

Figure 3.7: Maximum deceleration for the two Drives and for the two Conditions. Error bars = SEM.

Headway

There was a main effect of Drive on minimum headway [F(1,28)=7.343, p=.011, η_p^2= .208], being significantly shorter in the automated drive (M=15.31m, SE=2.72) than in the manual drive (M=22.75m, SE=3.47m). The result of this lower headway is also demonstrated by the higher collision count in the automated drives (Table 3). There was an effect of Condition for headway [F(1,28) = 5.679, p=.024, η_p^2= .169], with drivers in the heavy fog condition having a significantly shorter headway (M=12.96, SE=2.63m) compared to the light fog condition (M=17.66m, SE=2.81m), but this result needs to be interpreted cautiously because of the inter-group variance in headway in this between-subjects design. This is further supported by the differences in collision counts between the light fog and heavy fog conditions. There was a significant effect of Event for headway [F(1,28)=10.513, p=.003, η_p^2=.273] with shorter headway in the second critical event (M=15.27m, SE=2.98m), compared to the first (M=22.75m, SE=3.20m).

3.4 Summary and Conclusions

Previous studies on the human factors of the transition from HAD to manual driving have attributed less effective return-to-manual performance to the rather poorly understood human OoTL problem. To investigate the relative contribution of the driver OoTL state to driving performance during this transition, the current study attempted to simulate the driver OoTL state, and to examine whether it affected drivers' ability to recognise and respond to a critical situation.

We hypothesised that, by limiting system and environmental information during automation and prior to an automation uncertainty event, drivers would have a reduced ability to recognise and respond to a critical scenario. Eye glance data showed that during automation, when the screen was manipulated by a heavy fog condition, drivers were less engaged with the driving task and reduced their attention to the road centre. However, drivers were able to determine the criticality of the impending collision (critical events), disengaging automation after the lead vehicle braked in all but 8 of 60 cases. Yet, simply recognising the hazard did not seem sufficient, as drivers collided with the lead vehicle in 13 of 60 critical event cases. Drivers seemed to be more out of the loop in the heavy fog condition, with more collisions after this manipulation than the light fog condition (although differences were not significantly different).

In the study reported by Beller et al. (2013), communicating automation uncertainty was found to improve driver-automation interaction, such as an improved time to collision in the case of automation failure. They also report higher trust ratings and increased acceptance of the system. This study extends the work of Beller et al. (2013) by investigating the effect of such uncertainty on a higher range of vehicle control measures.

We found that when drivers were not in physical control of the vehicle and had an artificially reduced situation awareness during automated driving, their response to an impending collision after an uncertainty message in critical events involved greater maximum deceleration and higher maximum lateral accelerations, whilst they also maintained a shorter headway with the lead vehicle, when results were compared to manual driving performance. The response profile of drivers to a potential collision scenario was, therefore, less controlled and more aggressive immediately after the transition. Given that the uncertainty alarm was not a take-over-request but rather a request to monitor the system and intervene if they deemed necessary, it is difficult to accurately assess response time to an event. Nevertheless, taken together these differences suggest that following automation, drivers have a diminished capacity to respond as they would under normal manual control. Apart from the higher collision count in the heavy fog automation drive, driver response after the transition was found to be similar between the two screen manipulation conditions. However, it is not currently clear whether this lack of difference between the two levels of screen manipulation, aimed at taking drivers further OoTL, was an inappropriate application of the methodology, or whether the vehicle-based measures used to test this hypothesis were not robust enough to highlight any possible differences.

One of the challenges of using the screen manipulation technique to induce the OoTL state is that drivers are likely aware that they are losing information. In reality, when drivers are OoTL as a result of a distracting non-driving task or, indeed, vehicle automation, they may not know the extent to which they are OoTL. Therefore, the technique used in this study, may well be underestimating the effects of being OoTL in automation, on a driver's ability to respond in critical situations. In addition, as Dekker (2004) points out, the loss of situation awareness or deficient situation awareness is explained by reference to an "ideal", potential state of situation awareness, where one notices things that turn out to be critical. In the context of vehicle automation, this "ideal" is likely closely linked to drivers' understanding of the functionality and behaviour of the automated system. Before higher levels of vehicle automation become ubiquitous it is important for us to understand how drivers interact with their vehicle's automation system in dynamic environments, such that the design of these systems augment the limitations of the driver in this new context. Future studies on driver-automation interaction should, therefore, strive to integrate deeper context and meaning into the design of experiments and scenarios.

It is also pertinent to acknowledge that the measures used may be more meaningful when analysed according to the nature of the driver's response to a critical event.

For example, measures of lateral acceleration will be different for those who steer compared to those who only brake. Further studies are currently in progress in our laboratories to investigate these ideas in more detail by comparing the results from this study with other types of screen manipulation including the use of distracting tasks.

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CHAPTER 4

ARE YOU IN THE LOOP? USING GAZE DISPERSION TO UNDERSTAND DRIVER VISUAL ATTENTION DURING VEHICLE AUTOMATION

ABSTRACT This driving simulator study, conducted as part of the EC-funded AdaptIVe project, assessed drivers' visual attention distribution during automation and on approach to a critical event, and whether such attention changes following repeated exposure to an impending collision. Measures of drivers' horizontal and vertical gaze dispersion during both conventional and automated (SAE Level 2) driving were compared on approach to such critical events. Using a between-participant design, 60 drivers (15 in each group) experienced automation with one of four screen manipulations: 1) no manipulation, 2) manipulation by light fog, 3) manipulation by heavy fog, and 4) manipulation by heavy fog with a secondary task, which were used to induce varying levels of engagement with the driving task. Results showed that, during automation, drivers' horizontal gaze was generally more dispersed than that observed during manual driving. Drivers clearly looked around more when their view of the driving scene was completely blocked by an opaque screen in the heavy fog condition. By contrast, horizontal gaze dispersion was (unsurprisingly) more concentrated when drivers performed a visual secondary task, which was overlaid on the opaque screen. However, once they ceased and an uncertainty alert captures drivers' attention towards an impending incident, a similar gaze pattern is seen for all drivers, with no carry-over effects observed after the screen manipulations. This pattern was also seen for this period of manual driving. Results showed that drivers' understanding of the automated system increased as time progressed

and that scenarios that encourage driver gaze towards the road centre are more likely to increase situation awareness during high levels of automation.

4.1 Introduction

The past decade has seen a rapid development of vehicles equipped with Advanced Driver Assistance Systems (ADAS), culminating in multiple vehicle manufacturers releasing first-generation automated driving functionalities such as Lane Keeping Assist (LKA) and Adaptive Cruise Control (Level 2, partial automation; SAE, 2014). These include the Volvo XC90 (Volvo Cars, 2015), Tesla Model S (Tesla Motors, 2015), and Infinity Q50 (Infinity, 2015). While vehicle automation promises a number of social and individual benefits, including increased mobility (Rosenbloom, 2012), safety and efficiency (Anderson et al., 2014), it also shifts the driver's role, from that of an active operator to that of a passive supervisor (Merat et al., 2012). Some authors have suggested that this supervisory role takes drivers "out-of-the-loop" (OoTL) and impairs their ability to manage critical situations when performance after automation failure/limitations is compared to manual driving (Rudwin-Brown and Parker, 2004; Gold et al., 2013; Strand et al., 2014; Merat et al., 2014). While the origin of this OoTL concept is based on the effect of automation on performance within other domains (Weiner and Curry, 1980; Bainbridge, 1987; Norman and Orlady, 1989; Endsley and Kiris, 1995; Rasmussen and Rouse, 2013), the term is not yet currently well-defined when addressing the impact of vehicle automation on driving performance. Yet, from a human factors and road safety perspective, it is important to investigate the nature and consequences of this OoTL state and understand, for example, how it influences drivers' distribution of attention during high levels of automation, or how it affects their ability to resume control from automation in an appropriate and timely manner, should a system limit be reached. This paper, therefore, describes a driving simulator study that attempted to simulate the OoTL concept in vehicle automation and reports on the distribution of drivers' visual attention during SAE level 2 automation as a means of assessing this methodology.

According to Kienle et al. (2009), a driver is considered OoTL when they are "*not immediately aware of the vehicle and the road traffic situation because they are not actively monitoring, making decisions or providing input to the driving task*". Norman (1990) attributes causality not to automation per se but rather to a lack of continual feedback. The concept seems, therefore, to include two elements; one, which relates to the awareness of elements in the environment, and another, which relates to the awareness of elements regarding vehicle status and its automated system(s).

Seeking to expand on the mechanisms underlying the OoTL problem, Louw et al. (2015) presented a schematic representation of this concept, which proposes that, as a result of vehicle automation, drivers are removed from a physical control loop, because they are no longer physically interacting with the vehicle's mechanisms such as the steering wheel and pedals (see also Stanton and Young, 1998). Drivers can also be removed from a 'cognitive control loop' and lose situation awareness, either because they are looking away from the driving scene during automation and interacting with a distracting task, or due to boredom/mind-wandering (Lerner et al., 2015). Clearly, both loops are important for contributing to safe driving performance, since, for instance, physical neuromuscular control gives drivers feedback of steering torque and helps contribute to corrections of heading errors (Pick and Cole, 2006), whilst good situation awareness contributes to effective attentional control and decision-making and improves hazard perception, for instance, in response to critical events (Endsley, 2006; Horswill and McKenna, 2004). Accordingly, Louw et al. (2015) hypothesise that reductions in either or both aspects of control, brought about by automation, can contribute to less effective return-to-manual performance, but that not being in physical control can also act to impair situation awareness, which consequently can reduce driving performance.

To further investigate this concept, the current study sought to induce a range of OoTL states by removing driving-relevant information during automation and explored whether these affected drivers' ability to regain situation awareness in response to a potentially critical event. Based on the Kienle et al. (2009) definition, being in the loop involves three distinct elements: drivers must (i) be aware of the vehicle (ii) be aware of the road traffic situation and (iii) make decisions or provide input to the driving task (when resuming control). We, therefore, designed a study where we examined how drivers' ability to respond to potentially critical situations which followed a system-initiated automation disengagement, was affected by the systematic removal of the three elements mentioned above, thereby inducing an artificial OoTL state. This was achieved by developing a screen manipulation technique, introduced in Louw et al. (2015) and Louw et al. (2016), which uses a fog-like display to vary the degree of visual information available to drivers during automation, both in terms of the dashboard displays in the vehicle and also the road environment itself (see Figure 2, and Methods section for a more detailed outline). This approach broadly resembles a visual occlusion technique, first used by Senders et al. (1967) to model driver behaviour based on information theory, and then others to quantify the visual demand of in-vehicle information systems (Foley, 2008).

Extended durations of automated driving have been shown to take drivers further OoTL (Körber et al., 2015). However, here, we were simply interested in assessing whether removing driving-relevant information, with short periods of such screen manipulations, would take drivers OoTL, and what the effects of such manipulations would be on drivers' visual attention. Of course, one simple method for taking drivers OoTL (both physical and cognitive) is to allow interaction with a secondary task during automation. However, our rationale for using screen manipulations was to reduce the complications associated with the physical demand of engaging in a secondary task (Zeeb, Buchner, and Schrauf, 2015), which can take drivers' head, hands and eyes away from the driving scene (Carsten, Lai, Barnard, Jamson, and Merat, 2012; Louw, Merat, and Jamson, 2015) and adds considerable individual variability during the return to manual control.

Traditionally, analysis of drivers' performance in the transition period from automation to manual control has relied on the use of vehicle-based metrics and reaction time measures, following a mandatory resumption of control from a failing or limited automation system (Gold, Damböck, Lorenz, and Bengler, 2013; Louw et al., 2015; Merat and Jamson, 2008). However, while it is relevant to establish the minimum time required for drivers to resume control of the vehicle after automation disengagement (termed a take-over-response or TOR; see Beller et al., 2014; and Helldin et al., 2013), we argue that such instructions to resume control may simply be in response to alarms and experimenter commands, and not a reflection of drivers' recognition of, and ability to manage, an emerging critical situation. This argument is supported by Gold and colleagues' finding that while a relatively rapid resumption of control from automation is possible, where the first braking input can be as fast as 2.06 s, and steering input is around 2.27 s, it is at the cost of safe vehicle control (Gold et al., 2013). Therefore, our aim was to investigate drivers' assessment of the environment following a period of screen manipulation using an uncertainty alert, which declared the automation might not be able to handle the unfolding situation, and investigated how each screen manipulation condition affected drivers' ability to evaluate the criticality of events and decide whether resumption of control was necessary. We also assessed whether repeated exposure to such events influenced drivers' visual attention.

To assess drivers' attention to the driving scene and vehicle controls during, before and after each screen manipulation, we considered their visual attention to different areas of interest, using eye gaze dispersion. Psychophysiological research using eye gaze data has been a popular method for measuring drivers' attention allocation (Posner, 1980), situation awareness (Gugerty, 2011; Gartenberg et al., 2013) and hazard perception (Endsley and Jones, 2004; Horswill and McKenna, 2004). However, while gaze concentration has been used successfully in manual driving to distinguish between the effects of visual and cognitive load (Engström et al., 2005), it has been scarcely applied in automated driving (see for example Damböck et al., 2013, who report greater horizontal gaze dispersion for highly automated driving as compared to manual driving). A review of the literature by de Winter, Happee, Martens, and Stanton (2014), found that drivers in highly automated driving gaze on the road less often than when in manual control, which therefore could result in lower workload, but also poor situation awareness. However, most of the studies reviewed by de Winter et al. (2014) have used fixation-based Percentage Road Centre (PRC) measures (e.g. Carsten et al., 2012), rather than raw gaze data. According to Wang et al. (2014), fixation-based PRC is less sensitive to demand-induced changes in visual behaviour than measures of gaze-based PRC and gaze dispersion. Therefore, in this study, we chose to explore the use of horizontal and vertical gaze dispersion as a means of evaluating drivers' OoTL state during automated driving, as well as during the resumption of control from automation. The screen manipulation technique was used to induce varying levels of the OoTL state, by systematically removing information from drivers during automation. The study then considered the following questions:

1. What gaze pattern do drivers exhibit during each of the different screen manipulation conditions?
2. When resumption of manual control is required, is drivers' visual attention to the scene and vehicle controls affected differently by the different screen manipulations?
3. Can we infer drivers are taken out of the loop by the screen manipulations, and does this depend on the particular manipulations applied?

4. Does drivers' visual attention change after repeated exposure to the same events?

4.2 Methods

4.2.1 Participants

Following approval from the University of Leeds Research Ethics Committee (Reference Number: LTTRAN-054), four groups of 15 drivers were recruited via the driving simulator database and were paid £20 for taking part in the experiment. The average age of the participants was 36.16 $\pm$12.38 years, and out of 60 participants, 32 were male. Average mean annual mileage was 8290.46 $\pm$6723.08 miles. Participants had normal or corrected-to-normal vision, were required to have had a driving licence for at least one year (M = 16.22, SD = 12.92) and drive at least twice a week. Data from one participant was excluded from the analysis due to abnormal values from their eye-tracking data ($\pm$3 SD from the mean).

4.2.2 Design and Procedure

Materials

The experiment was conducted in the University of Leeds Driving Simulator, which consists of a Jaguar S-type cab with all driver controls operational. The vehicle is housed within a 4m spherical projection dome and has a 300° field-of-view projection system. A v4.5 Seeing Machines faceLAB eye-tracker was used to record eye movements at 60Hz.

Design

A repeated measures mixed design was used for this study, with a between-participant factor of Screen Manipulation (no fog, light fog, heavy fog, heavy fog + task) and within-participant factors of Drive Type (manual, automated) and Event Number (1-6).

The experimental session consisted of two drives for each group (manual, automated) which lasted about 20 minutes each, and participants experienced a short break between drives, to alleviate the symptoms of fatigue. Participants drove the

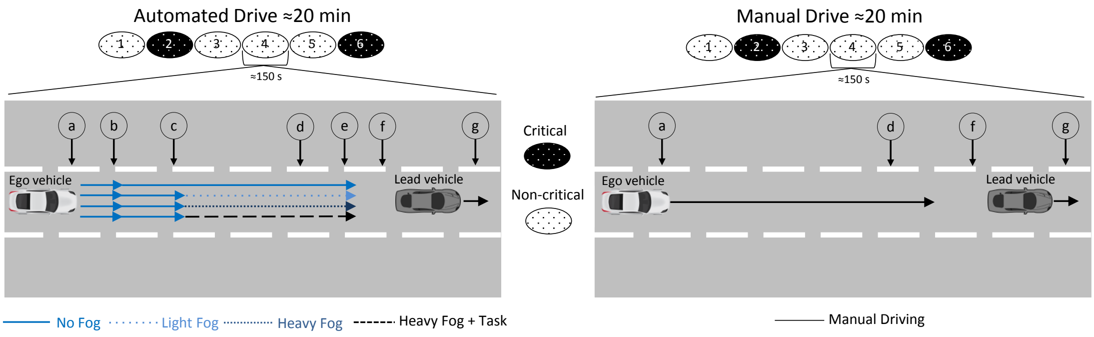


Figure 4.1: Schematic representation of each discrete event in the automated (left) and manual (right) drives. (a) to (g) represent various phases of the drive, as follows: (a) Event start, (b) Automation on, (c) Screen Manipulation on, (d) Drone moves into lane, (e) Screen Manipulations off + uncertainty alert, (f) Drone action, (g) Event end.

same road in both drives, but the screen manipulation was only used during the automated drives. For each Screen Manipulation group, the order of drives was counterbalanced across participants, with half of the participants performing the manual drive first and the automated drive second, and vice versa. As shown in Figure 1, within each automation and manual drive, there were six discrete car-following events, each lasting approximately 150 s. Our main aim here was to study drivers' response to critical events after they were taken OoTL with a screen manipulation. However, to assess situation awareness after the uncertainty events (see below), and to reduce priming, each drive contained only two critical events (events 2 and 6), interspersed with four non-critical events (events 1, 3, 4 and 5). During the non-critical events, the lead vehicle would either speed up or change lane, while during the critical events the lead vehicle decelerated at a rate of 5 m/s^2, resulting in an impending collision scenario. The time-to-collision (TTC) at the start of this deceleration was 3 s.

As outlined in the Introduction, to induce varying levels of the OoTL state during the automated drives, we employed four screen manipulation techniques (Figure 4.2). In the no fog condition, there was no manipulation of the road scene, and drivers could observed all aspects of the road and traffic environment. In the light fog condition, a translucent grey filter superimposed the road scene. The aim of this manipulation was to simulate a process whereby drivers were able to distinguish only basic elements of the road environment and the movement of vehicles in the immediate vicinity. In the heavy fog condition, an opaque grey filter overlaid the road scene. This manipulation sought to effectively blocked all visual information from the

(a) No Fog

(b) Light Fog

(c) Heavy Fog

(d) Heavy Fog + Task

Figure 4.2: Example of a drivers' view in the a) no fog, b) light fog, c) heavy fog, and d) heavy fog + task conditions.

road environment such that drivers were unaware of the traffic conditions. During the heavy fog + task condition the road was blocked with the same opaque grey filter used in the heavy fog condition but overlaid with a series of visually presented secondary tasks. Here, participants were required to complete a number of multiple-choice questions involving visuo-spatial shape-matching, general knowledge, and moderately challenging mathematics, which were sourced from various web-based IQ tests and were presented in a random order. All responses to this task were verbal. The aim of this manipulation was to assess how engagement in a secondary task affected performance, but since we were keen not to remove drivers' eyes and head away from the screen (keeping physical position as similar as possible to the other experiments) the secondary task was displayed on the driving scene, akin to a Head-Up Display. Participants were told that they would not be penalised for incorrect answers, but that their response would be recorded. We hypothesised that less visual information about the scene would take drivers further OoTL and that drivers, therefore, would be most OoTL during the heavy fog condition, followed by light fog and no fog conditions.

Procedure

Upon arrival, participants were briefed on the description of the study and were asked to sign a consent form, with an opportunity to ask any questions, if required. They were then given the opportunity to practice manual driving and Highly Automated Driving (HAD) within a free-flowing 3-lane motorway. During the practice session, participants were talked through the various aspects of the vehicle HMI Figure 4.3 were shown how to engage and disengage the automation and were also shown the screen manipulation they would encounter during the experimental automated drive. The road contained ambient traffic, but participants did not experience the critical events during the practice drives.

Regarding automation uncertainty, participants were told that should the automation become uncertain during the drive (see below for how this was portrayed) they should monitor the driving environment and determine for themselves whether or not to intervene. Participants were instructed to drive in the middle lane of the three-lane motorway for the duration of the drive (automation was only possible in this lane) but were permitted to change lane in critical situations, and were told to move back into the middle lane as soon as possible. Drivers were asked to obey the standard rules of the road and to ensure safe operation of the vehicle.

To engage the highly automated driving system, participants pressed a button on the steering wheel. To disengage automation, participants would either press the same button, turn the steering wheel more than 2° or press the brake pedal. During the automated drive, participants were asked to move to the centre of the middle lane as soon as convenient and then activate automated driving as soon as it was available. If drivers did not engage automation, the system engaged automatically after 5 s. The activation of automation constituted the start of an event. After 30 s of automated driving, one of four 90 s screen manipulations began. It is important to note that the vehicle dynamics, as well as all auditory cues, remained active during the screen manipulations. After each screen manipulation, the presence of a lead vehicle triggered an uncertainty scenario (for both critical and non-critical events). At this point, the screen manipulation concluded, the driving scene was again visible, and the automation status changed from "Engaged" to "Uncertain". Drivers were notified of this change by a short duration auditory tone (1000Hz, lasting 0.2 s), and the automation status symbol, which was now visible, changed from green to flashing yellow. The driver was expected to monitor the driving situation and intervene, if necessary. After 3 s, the lead vehicle completed one of three manoeuvres: In the non-critical event (1, 3, 4, 5) the lead vehicle either moved out of lane 2 or sped up, while in the critical events (2, 6) the lead vehicle braked sharply with a maximum deceleration of 5.0 m/s^2.

Human-Machine Interface (HMI)

The status of the vehicle's automated system was indicated by the colour of a steering wheel symbol that was located on the left panel of the central display unit (Figure 4.3). During the automated drives, the steering wheel symbol was solid green when automation was engaged, flashing yellow when it was uncertain and solid grey when it was unavailable. Any change to the automation state, whether driver- or system-initiated, was accompanied by the same non-intrusive auditory tone described above.

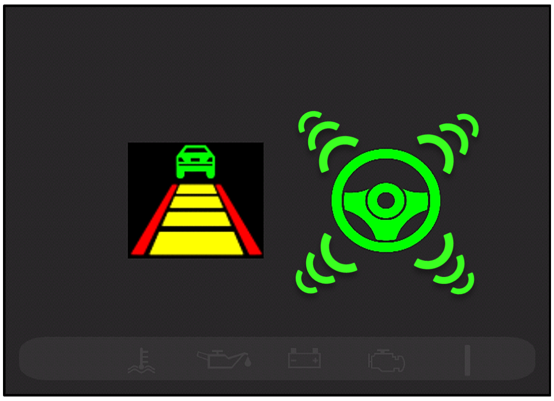


Figure 4.3: An example of the in-vehicle HMI with the Forward Collision Warning symbol on the left and the Automation Status Symbol on the right (flashing green in this example).

In addition to the automation status, a Forward Collision Warning (FCW) symbol was included in the left panel of the central display unit. Active only when automation was engaged, this system provided a visual approximation of the headway of the lead vehicle in seconds. In the automated drives, a continuous alarm alerted drivers of an imminent collision whenever TTC with the lead vehicle was below a 2 s threshold. However, this only occurred during the critical events. To further deprive drivers of system information during automation, the automation status (steering wheel) and the FCW were also hidden during the screen manipulation conditions. However, participants were able to reveal the HMI at any point by pulling the left indicator stick towards them. This action illuminated the HMI for 2 s. Participants were able to move this stick as often as they wished.

Research aim

Gaze dispersion was used to assess how drivers' visual attention was distributed in each of the four screen manipulation conditions and to study how visual attention to the vehicle and driving scene was affected by vehicle automation in each screen manipulation condition. We hypothesised that less visual information about the scene would take drivers further OoTL and that therefore drivers were most OoTL during the heavy fog condition, followed by light fog and no fog. To take drivers one stage further OoTL from the heavy fog condition, we distracted drivers by introducing a secondary task on the heavy fog screen. This was done in preference to using an in-vehicle display as we were keen not to dramatically change the position of the drivers' eyes, head and hand compared to the other conditions.

4.2.3 Statistical analyses

All data were analysed with IBM SPSS v21 (IBM Corp., 2012). Shapiro Wilk's test showed that not all estimates were normally distributed. As the data were moderately positively skewed, square root transformations were used for analyses (Tabachnick and Fidell, 2007). ANOVA results reported below are on the transformed responses, while the graphs represent estimates in the original units, to facilitate interpretation (Neter et al., 1990). An α-value of .05 was used as the criterion for statistical significance and partial eta-squared was computed as effect size statistics. Degrees of freedom were Greenhouse-Geiser corrected when Mauchly's test showed a violation of sphericity. Unless otherwise stated, variances of the data were homogenous, as assessed by Levene's test of equality of error variances (Field, 2009). Similarly, covariances of the data were homogenous, as assessed by Box's test of equality of covariance matrices, unless otherwise stated. LSD pairwise comparisons (α = .05) were used to determine the difference between levels of Screen Manipulation and Event Number.

As highlighted in the Introduction, we used drivers' gaze dispersion to establish

Table 4.1: Time windows used for statistical analyses.

Time Window	Start	End	Rationale	Comparisons
1	Automation On (b)	Screen Manipulation On (c)	Assess visual attention during uninterrupted driving	2 X 6 X 4 ANOVA: Drive Type (*automated, manual*) and Event Number (*1-6)* as within-participant factors and Screen Manipulation (*No Fog, Light Fog, Heavy Fog, Heavy Fog + Task*) as a between-participant factor
2	Screen Manipulation On (c)	Drone Moves Into Lane (d)	Assess the effect of the screen manipulations on visual attention	6 X 4 ANOVA: Event Number (*1-6)* as within-participant factors and Screen Manipulation (*No Fog, Light Fog, Heavy Fog, Heavy Fog + Task*) as a between-participant factor
3	Drone Moves Into Lane (d)	Screen Manipulation Off (e)	Not used for analysis	-
4	Screen Manipulation Off (e)	Lead Vehicle Action (f)	Assess the carry-over effect of the screen manipulations on visual attention	2 X 6 X 4 ANOVA: Drive Type (*automated, manual*) and Event Number (*1-6)* as within-participant factors and Screen Manipulation (*No Fog, Light Fog, Heavy Fog, Heavy Fog + Task*) as a between-participant factor 6 X 4 ANOVA: Event Number (*1-6)* as within-participant factors and Screen Manipulation (*No Fog, Light Fog, Heavy Fog, Heavy Fog + Task*) as a between-participant factor
5	Lead Vehicle Action (f)	Lead Vehicle Action (f) + 3 s	Assess the effect of a lead vehicle braking on visual attention	2 X 4 ANOVA: Critical Event (*2, 6)* as within-participant factors and Screen Manipulation (*No Fog, Light Fog, Heavy Fog, Heavy Fog + Task*) as a between-participant factor

how visual attention was distributed before and during each of the different screen manipulations. In addition, to understand how each manipulation affected this dispersion on approach to the six events, we considered how gaze dispersion varied just after the screen manipulations. To compare across the groups, we, therefore, divided each event into five Time Windows (TW), as in Figure 4.4. The rationale for these divisions and analyses are summarised in Table 4.1. Full statistical results are included in Table 4.2.

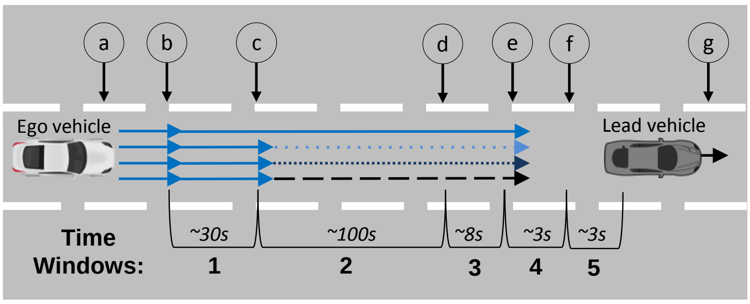


Figure 4.4: Schematic representation of the Time Windows used for the analyses. (a) to (g) represent various phases of the drive, as follows: (a) Event start, (b) Automation on, (c) Screen Manipulation on, (d) Drone moves into lane, (e) Screen Manipulations off + uncertainty alert, (f) Drone action, (g) Event end.

4.3 Results and Discussion

4.3.1 Gaze patterns during uninterrupted driving

Time Window 1 (TW1) was the only period in the automated drive where all drivers were able to see the road environment, which therefore allowed a comparison of performance with manual driving, and provided a reference point for the four screen manipulation conditions. For SD of Gaze Yaw, a three-way ANOVA showed a significant effect of Drive Type, where horizontal scanning was higher during automated driving compared to manual driving (M = 8.35°, SEM = .39° vs. M = 6.92°, SEM = .29°, respectively; Table 4.2). Our results are in line with findings from Damböck et al. (2013) and multiple other studies, which have used gaze PRC (de Winter et al., 2014) and find higher horizontal scanning by drivers during automation. This pattern of increased horizontal scanning can be seen in Figure 4.5(a)-4.5(b), which shows an example of density contour plots of gaze dispersion for the automated and manual drives during TW1, on approach to a non-critical event (Event 5). Analyses of variance did not find a significant effect of Screen Manipulation or Event Number for SD of Gaze Yaw, or any significant interactions. The primary plots illustrate a 40° vertical and horizontal field of view, where darker areas represent more concentrated gaze areas, while the histograms depict two-dimensional views of horizontal gaze concentration and the histograms to the right depict two-dimensional views of vertical gaze concentrations.

For SD of Gaze Pitch, a three-way ANOVA revealed no effect of Screen Manipulation or Drive Type (Table 4.2). There was a significant effect of Event Number for SD of Gaze Pitch, with Figure 4.6 showing that there was a gradual decrease across the experiment for both drives. However, the significant interaction of Drive Type and Event Number, also shown in Figure 4.6, suggests that the effect of Event Number is mainly due to the automated drives, as post-hoc tests showed that vertical gaze was significantly more dispersed in Event 1 compared to Events 2-5 ($p<.001$). This higher SD of Gaze Pitch for the first Event in automation was likely due to a familiarisation period, as drivers tried to assess their environment, looking ahead at the driving scene and back at the vehicle dashboard, which is then significantly reduced after the first Event. Also, whereas in the automated drive SD of Gaze Pitch continues to

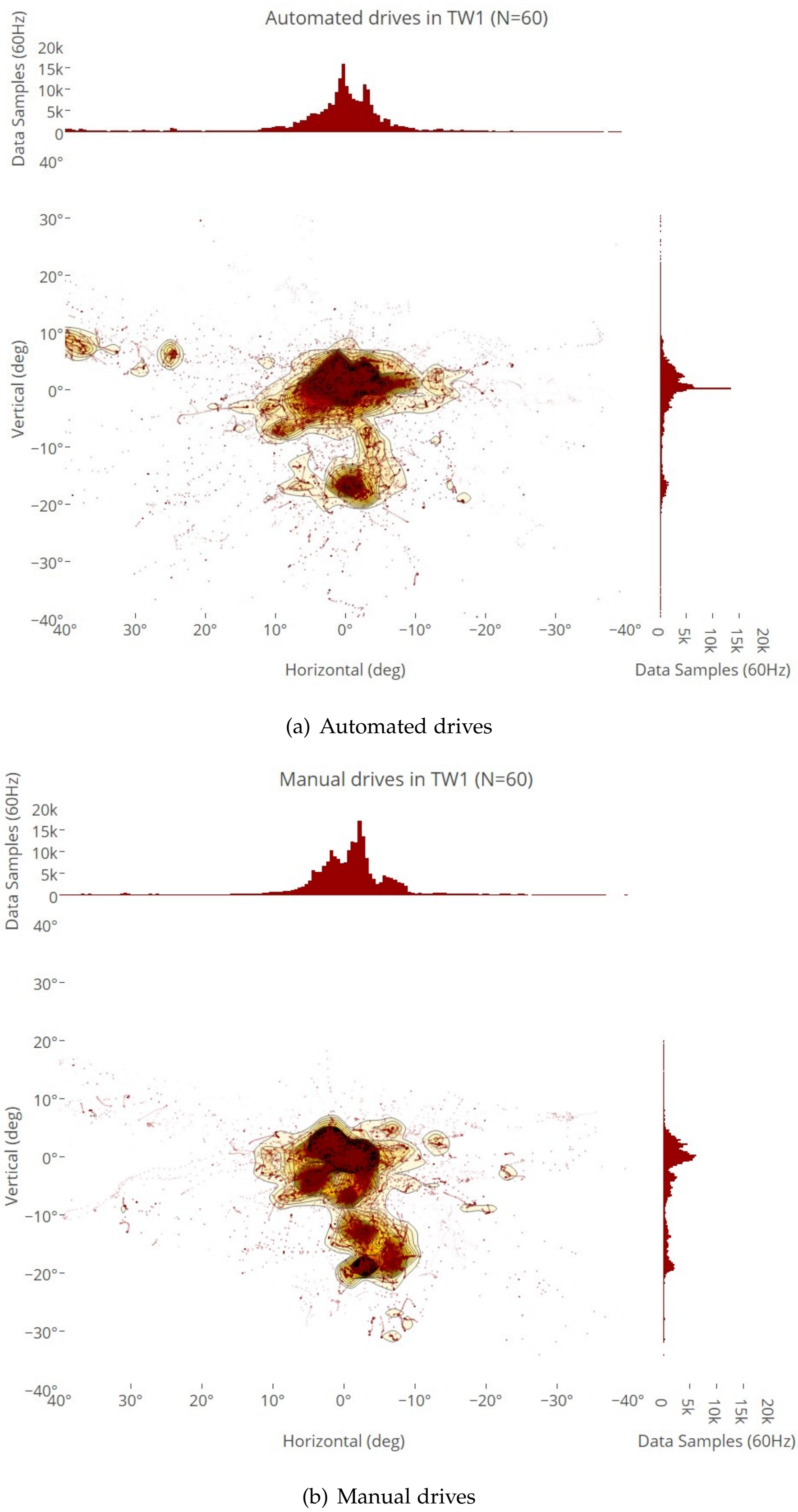


Figure 4.5: Example density contour plots of gaze dispersion in Time Window 1 (from "Automation On" to "Screen Manipulation On") for Event 5.

fluctuate over the course of the six events, in the manual drive the decrease is relatively consistent, which is likely due to the fact that, across all time windows, the manual drive was far less interrupted. Therefore, drivers seem to be looking between the lead vehicle and dashboard less during automation, perhaps attempting to assess the environment they do not control. In manual driving, drivers divided their attention between the lead vehicle and dashboard more, which could be because they were asked to maintain a speed of 70mph.

The slight increase in SD of Gaze Pitch in Event 3 for both the automated and manual drives is likely due to drivers' propensity to engage further in the driving task and glance more regularly between the road and vehicle console after experiencing the first critical event (Event 2).

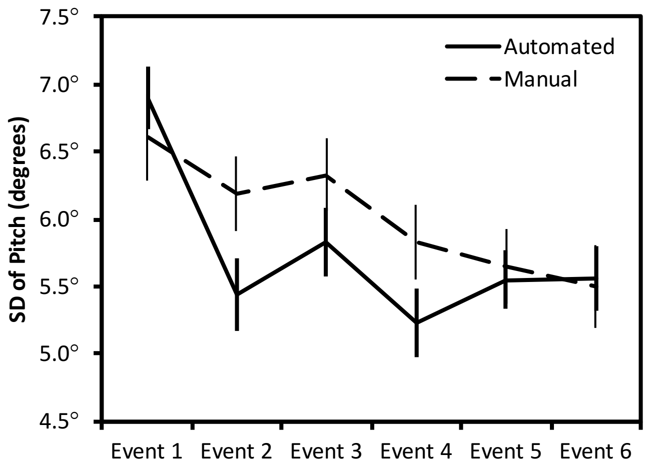


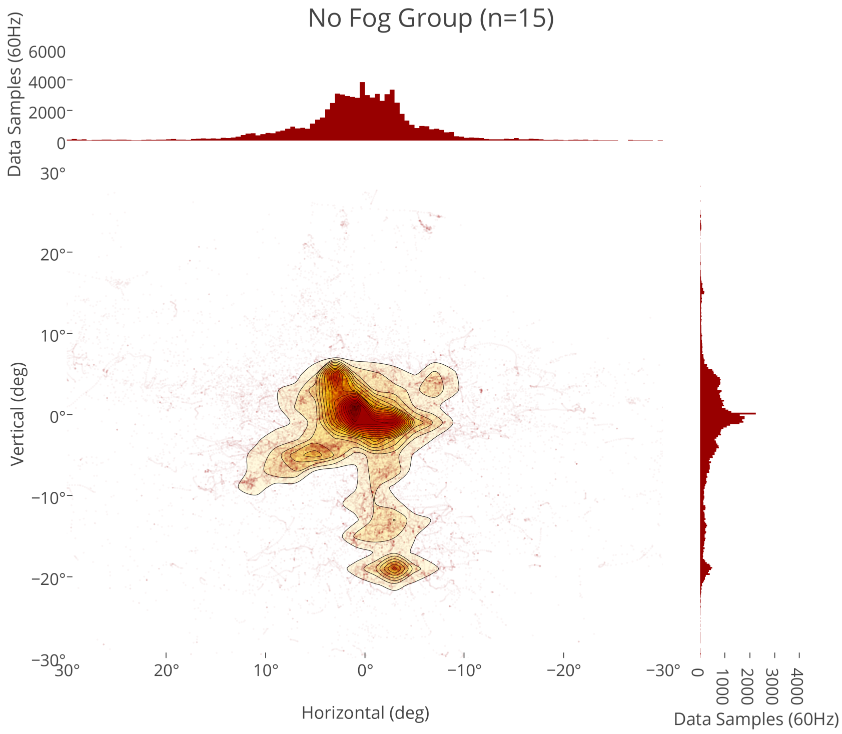
Figure 4.6: Mean SD of Gaze Pitch in Time Window 1 (from "Automation On" to "Screen Manipulation On") for each Event Number for the automated and manual drives.

4.3.2 Gaze patterns during the screen manipulations

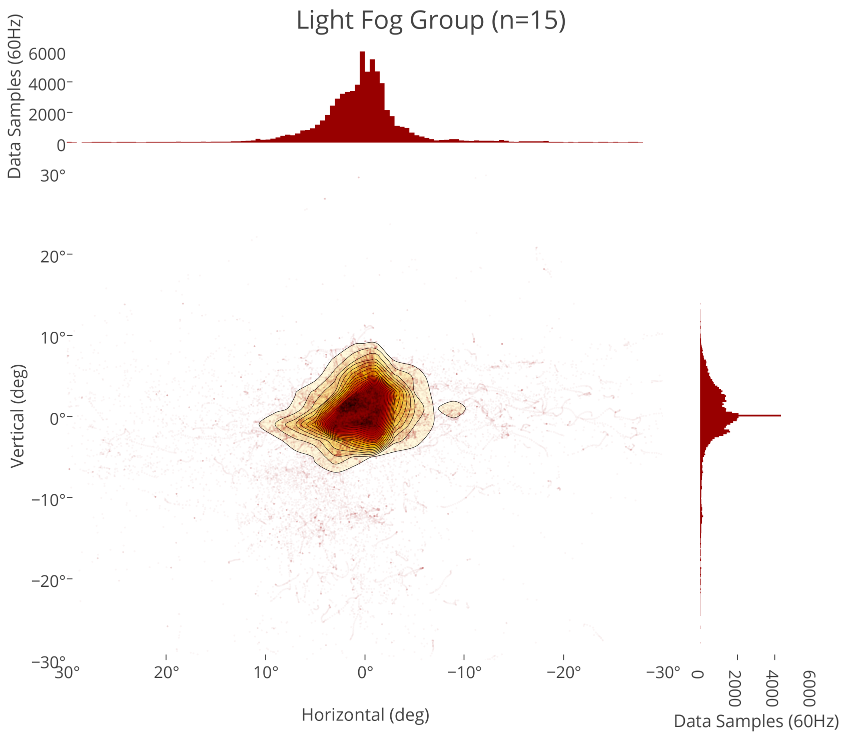
Time Window 2 (TW2) represents the period where the various screen manipulations were applied during the automated drives. Here, we expected changes to visual attention distribution as a result of these manipulations, and as a direct consequence of the degree of visual information available to drivers. To provide an overview of gaze distribution for the four Screen Manipulation conditions, Figure 4.7(a) to Figure 4.8(b) displays density contour plots for all participants during TW2 for each Manipulation. Whereas these figures show raw gaze distribution, analysis was conducted on the mean standard deviation of gaze (e.g., Figure 4.9). Therefore, while the patterns in Figure 4.9 loosely correspond to the patterns in Figure 4.7(a) to Figure 4.8(b), the latter are intended only as a visual guide.

A two-way ANOVA was conducted on the SD of Gaze Yaw to assess the effect of each screen manipulation during automation (Table 4.2). Results showed a significant main effect of Screen Manipulation, as shown in Figure 4.9. Post-hoc analyses revealed this was due to the different horizontal scanning pattern of drivers during the No Fog and Heavy Fog + Task conditions ($p < .05$). This reduction of horizontal gaze because of the secondary task engagement is not surprising and cannot in itself be used as a direct indication of how much drivers were OoTL. Figure 4.9 also shows similar horizontal scanning when drivers were able to see the driving scene in the No Fog condition and when the scene was fully occluded during the Heavy Fog condition. There was no effect of Event Number ($p = .664$) for SD of Gaze Yaw and no interaction between Event Number and Screen Manipulation, suggesting that the screen manipulations had a consistent effect on horizontal scanning throughout the six Events for all screen manipulations ($p = .92$).

A two-way ANOVA for SD of Gaze Pitch also showed a main effect of Screen Manipulation, with the greatest vertical gaze dispersion seen for drivers in the Heavy Fog condition. Post-hoc analyses found significant differences between this condition and all other screen manipulation conditions (Figure 4.10), suggesting that when drivers were taken OoTL by not being able to see the the road, their primary vertical gaze activity focused on looking between the road ahead and the vehicle dashboard, presumably awaiting the end of the screen manipulation. There was also a main effect of Event Number for SD of Gaze Pitch. As can be seen in Figure 4.11, pairwise comparisons revealed that this effect was due to an increased concentration of vertical scanning after Event 1, which is significantly higher than all but the last Event ($p<.05$). As with TW1, the higher SD of Gaze Pitch for Event 1 is likely due to a familiarisation period by drivers, at the start of the drive. There was no interaction between Event Number and Screen Manipulation for SD of Gaze Pitch.

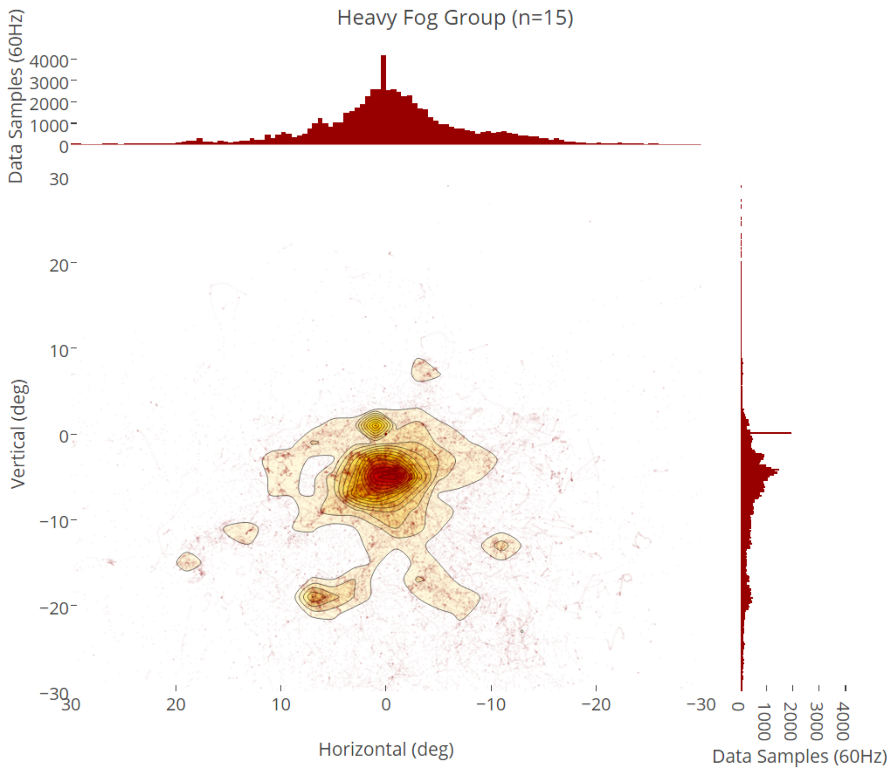


(a) No Fog

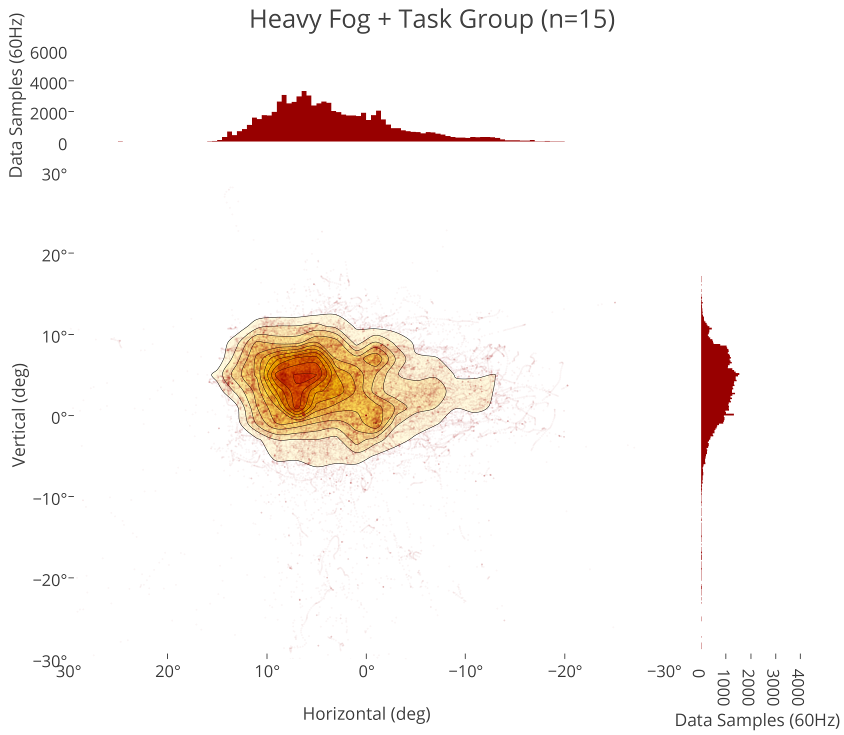


(b) Light Fog

Figure 4.7: Density contour plots of gaze for the No Fog and Light Fog groups in Time Window 2 (from "Screen Manipulation On" to "Drone Moves into Lane") for all events in the automated drive.



(a) Heavy Fog



(b) Heavy Fog + Task

Figure 4.8: Density contour plots of gaze for the Heavy Fog and Heavy Fog + Task groups in Time Window 2 (from "Screen Manipulation On" to "Drone Moves into Lane") for all events in the automated drive.

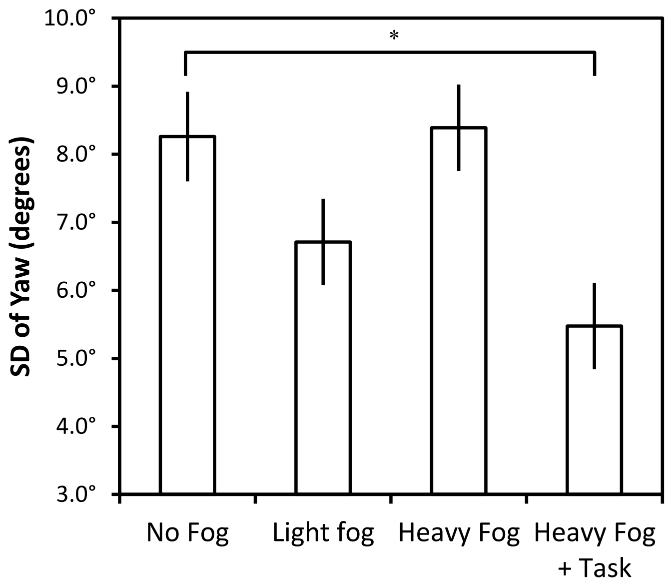


Figure 4.9: Mean SD of Yaw during Time Window 2 (from "Screen Manipulation On" to "Drone Moves into Lane") for each of the four automated drives (*p<.05).

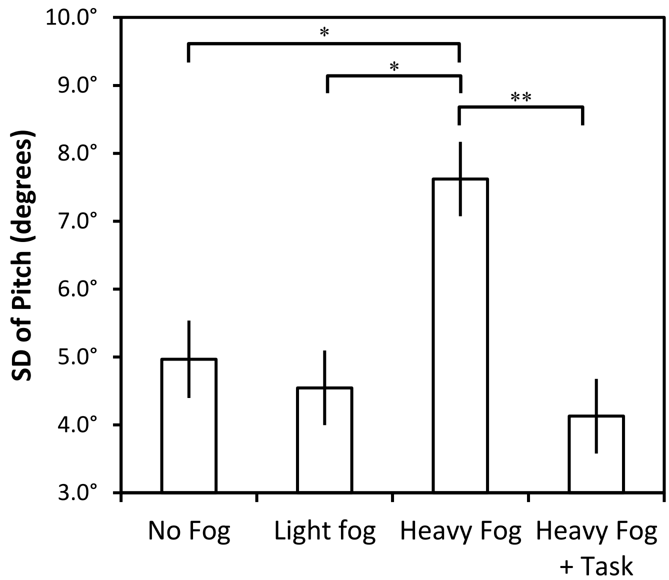


Figure 4.10: Mean SD of Pitch during Time Window 2 (from "Screen Manipulation On" to "Drone Moves into Lane") for each of the four automated drives (*p<.05, **p<.001).

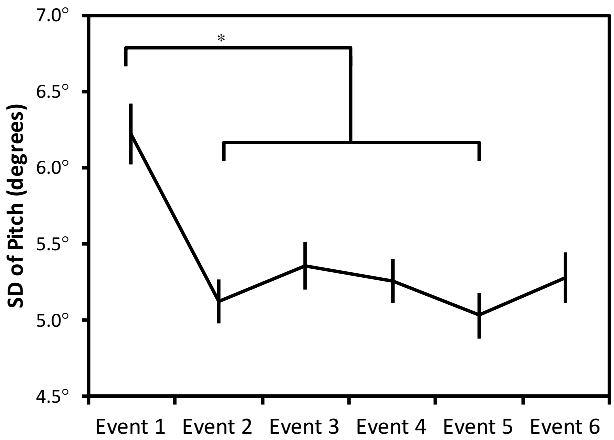


Figure 4.11: SD of Gaze Pitch across all events in the automated drive for Time Window 2 (from "Screen Manipulation On" to "Drone Moves into Lane"). Asterisks indicate that, for SD of Gaze Pitch in the automated drive, Event 1 is significantly different to Events 2-5 (*p<.05).

4.3.3 Gaze patterns pre-screen manipulations

Time Window 3 (TW3) constituted an 8 s period where the manipulations in TW2 continued in the automated drives, but where surrounding vehicles began to move into place to trigger an uncertainty event. TW3 was excluded from the analyses, since drivers' eye movements were likely to be affected by the movement of surrounding vehicles when the road scene was visible.

4.3.4 Gaze patterns post-screen manipulations

Time Window 4 (TW4) constituted a 3 s period from the end of the screen manipulations (which coincided with the start of the uncertainty alert in automation) up to the moment before the lead vehicle either braked, changed lane, or sped up. This period allowed for the assessment of drivers' gaze patterns during a Situation Awareness Recovery period (SAR; Gartenburg et al., 2013), defined as the process of restoring SA after SA has been reduced. A 3-way ANOVA revealed no differences between the automated and manual drives for either SD of Gaze Yaw ($p = .130$) or SD of Gaze Pitch ($p = .160$), suggesting that regardless of the screen manipulation, drivers recovered quite quickly, at least as indicated by their visual attention to the road ahead.

To investigate any carry-over effects of the four screen manipulations on gaze patterns, a 2-way ANOVA was conducted on SD of Gaze Yaw and Pitch for the automated drives only. Results showed that horizontal and vertical gaze dispersion was the same for all Screen Manipulations, in the three seconds immediately after screen manipulation was removed. These results suggest that when drivers' attention was captured by the uncertainty alert, their visual attention to the road ahead was not affected by the previous screen manipulation. Therefore, regardless of the degree of visual information available to drivers during each screen manipulation the same pattern of horizontal and vertical gaze scanning was observed in preparation for response to the lead vehicle.

Analyses of variance also showed that while there was no effect of Event Number for SD of Gaze Yaw in the automated drives ($p = .450$), there was a significant effect of Event Number for SD of Gaze Pitch ($p < .05$). Patterns were similar to that seen during Time Windows 1 and 2 and likely due to drivers' familiarisation with the driving scenarios, after Event 1.

4.3.5 Gaze patterns post-Brake light

Time Window 5 (TW5) constituted a 3 s period after first onset of the lead vehicle's brake light. Only gaze patterns for the two Critical Events were considered for this analyses, as these events required direct intervention by drivers, which would otherwise result in a collision.

A 3-way ANOVA showed that, there was no effect of Drive Type ($p = .225$) or Screen Manipulation ($p = .067$) on SD of Gaze Yaw (Table 4.2). There was, however, a significant difference in horizontal scanning between the two critical events, with lower SD of Gaze Yaw in the first ($M = 5.26°$, $SEM = .403°$) compared to the second ($M = 6.30°$, $SEM = .51°$) critical event. The ANOVA also revealed a significant interaction between Drive Type and Event Number for SD of Gaze Yaw. Although horizontal scanning was relatively high for both events in the manual conditions, in the automated drive it increased from 4.03° ($SEM = .47°$) in Critical Event 1 to 6.83° ($SEM = .51°$) in Critical Event 2 (Figure 4.12). This suggests a learning effect in the automated drives, where drivers understood the significance of a potential collision in the first critical event and scanned the environment and particularly the adjacent lane more extensively on approach to the second critical event to prepare for a suitable response, such as changing lane. Clearly, the same degree of horizontal scanning occurred for both Events in manual driver, when drivers were in control of the vehicle and responsible for lane changing.

For SD of Gaze Pitch, there was no effect of Drive Type (p = .064) or Screen Manipulation (p = .095), suggesting that drivers' vertical gaze distributions just before response to the braking lead vehicle were the same in the manual and automated drives and across the four conditions. There was also no effect of Event Number for SD of Gaze Pitch, suggesting that the screen manipulations did not have a carry-over effect on vertical gaze patterns, once the lead vehicle braked in the Critical Incidents.

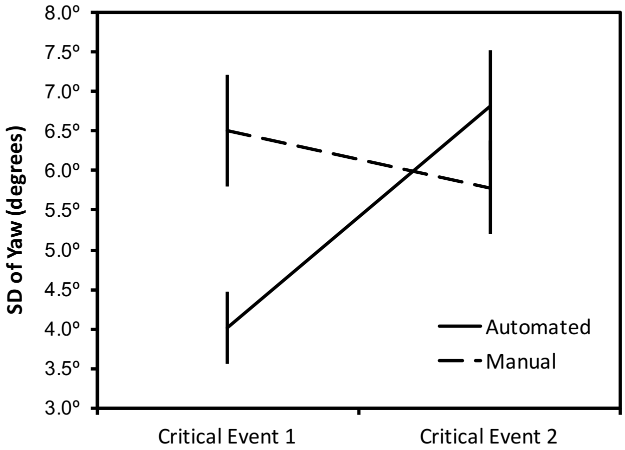


Figure 4.12: Mean SD of Gaze Yaw for Critical Event 1 and Critical Event 2 in the Automated and Manual drives, for Time Window 5 (from "Drone Action" to "Event End".)

Table 4.2: Results for ANOVAs conducted for each Time Window for SD of Gaze Yaw and SD of Gaze Pitch.

Effect		Drive Type		Event Number		Screen Manipulation		Drive Type*Event Number		Drive Type*Screen Manipulation		Event Number*Screen Manipulation	
		$F(df1, df2)$	η_p^2	$F(df1, df2)$	η_p^2	$F(df1, df2)$	η_p^2	$F(df1, df2)$	η_p^2	$F(df1, df2)$	η_p^2	$F(df1, df2)$	η_p^2
TW1 - 3-way ANOVA	SD of Gaze Yaw	19.9(1,55)**	0.27	n.s.		n.s.		n.s.		n.s.		2.0(15,275)*	0.10
	SD of Gaze Pitch	n.s.		20.2(4.12,234.81)**	0.27	n.s.		2.7(5,280)*	0.05	n.s.		n.s.	
TW2 - 2-way ANOVA	SD of Gaze Yaw	N/A		n.s.		4.6(3,56)*	0.19	N/A		N/A		n.s.	
	SD of Gaze Pitch	N/A		6.6(3.73,208.79)**	0.11	7.6(3,56)**	0.30	N/A		N/A		n.s.	
TW4 - 3-way ANOVA	SD of Gaze Yaw	n.s.		2.3(5,280)*	0.04	n.s.		n.s.		n.s.		n.s.	
	SD of Gaze Pitch	n.s.		5.7(5,280)**	0.09	n.s.		2.9(5,280)*	0.05	n.s.		n.s.	
TW4 - 2-way ANOVA	SD of Gaze Yaw	N/A		n.s.		n.s.		N/A		N/A		n.s.	
	SD of Gaze Pitch	N/A		9.4(5,280)** [1]	0.14	n.s.		N/A		N/A		n.s.	
TW5 - 3-way ANOVA	SD of Gaze Yaw	n.s.		5.1(1,55)* [1]	0.09	n.s.		5.9(1,55)* [1]	0.10	n.s.		n.s.	
	SD of Gaze Pitch	n.s.		n.s.		n.s.		n.s.		n.s.		n.s.	

* p < .05 ** p < .01 [1] Critical Events only (2, 6)

4.4 Conclusions

Previous studies have suggested that drivers' inability to respond effectively to critical scenarios following limitations or failures of highly automated driving (SAE Level 2) is because they are 'out-of-the-loop' (OoTL). In these studies, when performance in automated driving is compared to manual driving, reaction time to critical incidents is slower, sometimes leading to crashes, and drivers are generally less aware of their surroundings, presumably taking some time to reorient their attention to the driving scene after automation is disengaged. However, there is currently no consensus as to what constitutes an OoTL driver, how this state is measured, and what information drivers use to remain engaged with the driving task. To address these issues, we manipulated the simulated driving scene in a series of conditions, by removing driving-relevant visual information for short periods, and investigating driver behaviour and gaze patterns before, during and after such manipulations. Drivers' visual attention to unfolding critical and non-critical events after such manipulations were also studied and findings were compared to driving with manual control.

Results showed that, during automation, drivers' vertical gaze was most dispersed when the road scene and dashboard were completely occluded during automation (heavy fog condition). Here, drivers systematically moved their gaze between the road ahead and the vehicle dashboard, presumably in preparation for the resumption of control. Horizontal gaze dispersion was also highest in this drive. In contrast, and against our expectations, when the road scene was partially occluded during the light fog condition, drivers' gaze was almost entirely on the road centre, and they seemed to ignore the vehicle HMI. Therefore, by withholding only some information, drivers were seen to remain more engaged in the driving task, compared to if all information was removed. Focus of gaze towards the road scene and infrequent gaze towards the HMI was also high when a secondary task was present on the driving scene during automation.

These gaze dispersion patterns provide some understanding of what information drivers use to keep themselves engaged in the driving task during automation, and what information they use to keep in the loop when they have access to only some driving-relevant information. In other words, when they can see the scene for themselves, drivers distribute their gaze towards a larger area of the driving scene and surrounding environment, presumably, because they can easily see any unfolding events and believe they can rapidly resume control from automation, if required. Perhaps they can afford to trust the automation more in this condition as resumption of control is easier, in the event of a failure. When this information is completely removed, attention is also spread horizontally across the driving scene but also heavily between the vehicle HMI and the road. This increase in vertical gaze, especially, is likely to allow drivers access to maximum information from all relevant sources, for resumption of control. Taken together, these results may suggest that, if relevant vehicle information is presented in the dashboard area, then vertical dispersion of gaze is likely to be higher when drivers are OoTL.

When the road scene was only partially visible, drivers clearly believed visual attention was best placed towards the area of the likely incident, the road centre, and that less valuable information was available from the HMI. Here, drivers probably trusted the automated system least and wished to rely on their own skills for resumption of control. Finally, when required to engage in a secondary task, drivers prioritised this task, perhaps to the detriment of driving, also taking their attention away from the HMI - when the road scene was not visible.

Perhaps fortunately, this study revealed that regardless of these screen manipulations, when an uncertainty alert captures drivers' attention towards an impending incident, a similar gaze pattern is seen for all drivers, with no carry-over effects observed after the screen manipulations, and similar gaze patterns also seen for this period of manual driving. Therefore, while these short periods of screen manipulation may well disperse drivers' visual attention away from the road centre, they do not have a long lasting effect on visual attention to the point of danger, when response is required before a potentially critical event.

While the focus of this paper was to induce varying degrees of being OoTL and assess their concomitant effect on drivers' gaze dispersion, the effect of such gaze patterns on ensuing performance is perhaps worth considering. Although not reported here, an analysis of driving performance suggests that those screen manipulations which caused the most gaze dispersion (no fog and heavy fog) were followed by the highest number of collisions (Louw et al., 2016). These results illustrate, therefore, that scenarios that encourage driver gaze towards the road centre are likely to bring drivers back into the loop more efficiently by facilitating better situation awareness/hazard perception during the transfer of control from highly automated driving. Although further work is required to validate this proposal, these findings suggest that any information presented to drivers during automation should be placed near the centre of the road, akin to a Head Up Display. Clearly, the interaction between presenting such information towards the road centre during automation, and the consequent effect on driver distraction, needs further investigation.

An encouraging finding from these studies was that, regardless of screen manipulation, drivers' understanding of the automated system and uncertainty events increased as time progressed. This was illustrated by observations in vertical gaze dispersion, which was significantly reduced after the first event. There was also an increase in horizontal dispersion of gaze upon approach to the second critical event in automation; suggesting drivers prepared themselves, for instance by looking towards the adjacent lane before a lane change, to avoid collision with the lead vehicle.

It is important to note that the manipulations used in this study do not provide a complete assessment of the OoTL state. As disengagement from the driving task was involuntary and experimenter-induced, the effects are likely underestimated. Under normal automated driving conditions, drivers' withdrawal of attention, and therefore disengagement from feedback of driving relevant information, is generally self-induced and voluntary. Maintaining consistent and voluntary disengagement from all aspects of the driving task in a controlled setting highlights a key challenge in attempting to investigate the OoTL state. Moreover, gaze dispersion is only one of several measures that should be examined to investigate whether automation unduly impedes drivers' abilities to regain full cognitive and physical control. Therefore, natural progressions of this work are to analyse how drivers' visually process road hazards in critical takeover scenarios, and to establish how well calibrated drivers' vehicle control is to the criticality of an unfolding scenario, following a takeover. Future studies should also consider the effect of longer periods of placing drivers OoTL on such measures, as well as HMI solutions that provide informative, yet non-intrusive system feedback.

4.5 Acknowledgements

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CHAPTER 5

WERE THEY IN THE LOOP DURING AUTOMATED DRIVING? LINKS BETWEEN VISUAL ATTENTION AND CRASH POTENTIAL

ABSTRACT A proposed advantage of vehicle automation is that it relieves drivers from the moment-to-moment demands of driving, to engage in other, non-driving related, tasks. However, it is important to gain an understanding of drivers' capacity to resume manual control, should such a need arise. As automation removes vehicle control-based measures as a performance indicator, other metrics must be explored. This driving simulator study, conducted under the EC-funded AdaptIVe project, assessed drivers' gaze fixations during partially-automated (SAE Level 2) driving, on approach to critical and non-critical events. Using a between-participant design, 75 drivers experienced automation with one of five out-of-the-loop (OoTL) manipulations, which used different levels of screen visibility and secondary tasks to induce varying levels of engagement with the driving task: 1) no manipulation, 2) manipulation by light fog, 3) manipulation by heavy fog, 4) manipulation by heavy fog plus a visual task, 5) no manipulation plus an n-back task. The OoTL manipulations influenced drivers' first point of gaze fixation after they were asked to attend to an evolving event. Differences resolved within one second and visual attention allocation adapted with repeated events, yet crash outcome was not different between OoTL manipulation groups. Drivers who crashed in the first critical event showed an inconsistent pattern of eye fixations towards the road centre on approach to the event, while those who did not demonstrated a more stable pattern. Automated driving systems should be able to direct drivers' attention to hazards no less than 6 seconds in advance of an adverse outcome.

5.1 Introduction

The first generation of partially-automated vehicles (SAE Level 2; SAE, 2014) is already on our roads. The Volvo XC90, for example, combines Lane Keeping Assist (LKA) and Adaptive Cruise Control (ACC) in 'IntelliSafe Autopilot' mode (Volvo Cars, 2016). However, drivers are still required to supervise the system and resume control, for instance due to system limitations. Studies suggest that prolonged monitoring of an automated system can take drivers out of the loop (Merat et al., 2014), inducing passive fatigue (Desmond and Hancock, 2001), thereby reducing drivers' attentional capacity (Desmond and Matthews, 1997) and ability to detect, evaluate and respond to critical events thus increasing the likelihood of crashes (Endsley, 1995; Hollnagel and Woods, 2005; de Winter et al., 2015). Concomitantly, drivers may choose to engage in non-driving related activities (Carsten et al., 2012), which distract from the supposed primary task of monitoring the vehicle. Therefore, passive fatigue and task disengagement are two factors that may hamper drivers' ability to safely resume control from an automated system in driving (Neubauer et al., 2014; Merat et al., 2012).

Previously, in a series of studies designed to investigate this concept, we used various OoTL manipulation techniques, including altering drivers' visibility of the road scene during automation while they completed visual and non-visual tasks, thereby varying drivers' level of awareness and engagement in the driving task (Louw et al., 2015; Louw and Merat, 2017). We found a differential effect of OoTL manipulation on the standard deviation of horizontal gaze position, where drivers looked around more when their view of the driving scene was completely blocked, and horizontal gaze was more concentrated when drivers performed a visual secondary task presented on the road scene, but these differences actually resolved within three seconds after removal of the OoTL manipulation. However, while gaze dispersion provides an overview of drivers' visual attention, it is not as informative as point and duration of eye fixations for identifying the focus of drivers' visual attention. That is, where and for how long drivers are fixating in the driving scene or car cabin.

Previous studies have shown that sudden changes to the road environment capture drivers' attention, resulting in reduced visual scanning of the scene and increased fixations towards changes therein (Chapman and Underwood, 1998; Velichkovsky et al., 2002) which link directly to an increase in crashes (Crundall, Shenton, and Underwood, 2004). Therefore, this study considered drivers' eye fixations in the seconds after removal of the OoTL manipulations, to assess how each manipulation affected the pattern of visual attention allocation, and whether this was predictive of drivers' ability to avoid crashes in critical scenarios. Finally, although many studies have considered driver behaviour after take-over from automation in response to a take-over request (Gold et al., 2013; Louw, Merat, and Jamson, 2015) we introduced an 'uncertainty alert' in this study to portray potential system limitation, which required drivers to assess the need to resume manual control, allowing us to evaluate drivers' trust in the system, assessing their visual attention on approach to each of the six events.

5.2 Methods

5.2.1 Participants

75 drivers (41 male), aged 21-69 years (M=36.16, SD=12.38) were recruited via the participant database of the fully motion-based University of Leeds Driving Simulator (UoLDS) and were reimbursed £20 for partaking. Participants had normal or corrected-to-normal vision, an average annual mileage of 8290.46 (SD=6723.08), a full driving licence for at least three years (M=16.22, SD=12.92), and drove at least twice a week.

5.2.2 Design and Procedure

Materials

The experiment was conducted in the UoLDS, which consists of a Jaguar S-type cab housed in a 4m spherical projection dome with a 300° field-of-view projection system. A v4.5 Seeing Machines faceLAB eye-tracker was used to record eye movements at 60Hz.

Design

A 5 X 2 repeated measures mixed design was used, with OoTL Manipulation (No Fog, Light Fog, Heavy Fog, Heavy Fog+Quiz, No Fog+n-back) as between-participant factor and Event Number (1-6) as within-participant factor. The automated drive lasted about 20 minutes and encompassed six discrete car-following events, within a free-flowing three-lane motorway with ambient traffic. As shown in Figure 6.3, the drive contained two critical events (2,6), where the lead vehicle decelerated at a rate of 5.0 m/s^2 with a 3 s time-to-collision (TTC), and four non-critical events (1,3,4,5), where the lead vehicle either sped up or changed lane. Crash with the lead vehicle was inevitable in the critical events, if drivers failed to resume control. Participants completed two experimental drives, a manual drive and an automated drive, which were counterbalanced across participants. As this paper is focused on comparing the effect of different types of OoTL manipulation on performance in automation, results from the manual drive are not included.

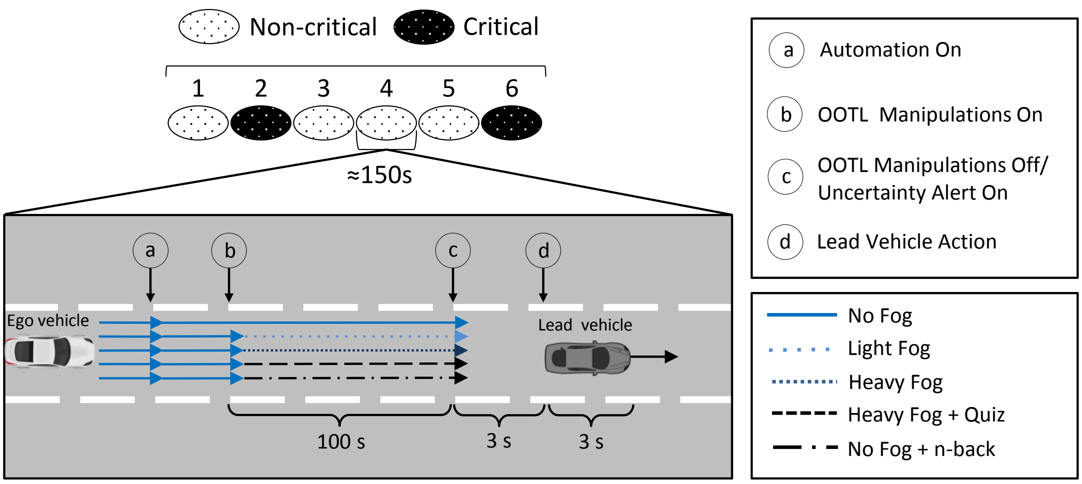


Figure 5.1: Schematic representation of each discrete event in the experimental drive. (a) to (d) represent various phases of the drive.

Automated Driving System

The partially-automated driving (PAD) system was only available when the vehicle was travelling between 65 and 75 mph in the middle lane. The system was engaged via a button on the steering wheel and disengaged by either pressing the same button, turning the steering wheel more than 2°, or depressing the brake pedal. If participants did not engage automation, the system engaged automatically after 5 s. Once engaged, the system assumed lateral and longitudinal control and adjusted the vehicle's speed to maintain 70mph.

Automation status was indicated by the colour of a steering wheel symbol located in the vehicle's central display unit. It was solid grey when automation was unavailable, flashed green when available, and appeared solid green when active. A flashing yellow symbol indicated automation was 'uncertain', and drivers were expected to monitor the roadway and intervene if they deemed necessary (see Louw and Merat (2017) for further details of the HMI). If the driver deactivated the automation, the symbol appeared solid red for 2 s. Automation activation and deactivation was accompanied by an auditory tone (1000Hz, 0.2 s). A forward crash warning symbol included to the left of the automation status symbol gave drivers a visual estimate of the lead vehicle headway and a continuous alarm sounded if drivers reached a 2 s TTC.

OoTL Manipulations

To vary the level by which drivers were aware of, and engaged with, the driving task during automation, we applied one of five OoTL manipulation techniques to briefly alter their vision of the road scene. In the No Fog condition, the road scene was not manipulated in any way. In the Light Fog condition, a translucent grey filter superimposed the road scene, allowing drivers to perceive elements in the road environment in the immediate vicinity, but not further afield. This manipulation aimed to simulate situations where drivers' primary focus towards the OoTL is partially hindered due to interaction with other non-driving related tasks. In the Heavy Fog condition, an opaque grey filter overlaid the road scene, blocking all visual information from the road environment, with the aim of simulating situations where the driver is completely looking away from the road scene and is unaware of the traffic conditions. In the Heavy Fog+Quiz condition, a visually presented secondary task was overlaid on the opaque grey OoTL, and participants were required to provide verbal answers to a series of multiple-choice questions relating to visuospatial shape-matching, general knowledge questions, and moderately challenging mathematics. These questions were sourced from various web-based IQ tests and were used to assess how a visual secondary task affected performance. In the No Fog+n-back task condition, there was no OoTL manipulation, and participants completed the verbal response delayed digit recall task (n-back; Mehler et al., 2011; Kirchner, 1958) during automation. Participants were presented with a sequence of single digit numbers and were expected to repeat out loud the last number presented. This was used to assess how engagement in a non-visual task during automation would affect eye-movements, resumption of control and crash avoidance.

Procedure

Upon arrival, participants read a handout with details of the experiment. After signing consent, participants completed a 15-minute familiarisation drive, consisting of non-critical events only. This began with a short manual drive. Once familiar with the simulator controls, participants practised activating/deactivating the automation, were shown how the HMI communicated automation states, and experienced the OoTL manipulations. Participants then completed the two experimental drives.

Data Analysis

Data were analysed with SPSS V.21 (IBM, Armonk, NY, USA). A α-value of .05 was used as the criterion for statistical significance and partial eta-squared (η_p^2) was computed as an effect size statistic. Least Significance Difference (LSD) pairwise comparisons (α= .05) were used to determine the difference between levels of OoTL Manipulation and Event Number.

5.3 Results and Discussion

Our aim was to explore drivers' visual attention during the resumption of control from PAD, after experiencing different OoTL manipulations designed to vary drivers' awareness of, and engagement with, the road scene. The following research questions were addressed: (i) how does each OoTL Manipulation affect the location of drivers' first fixation after the uncertainty event, (ii) how are drivers' fixations distributed over time, and (iii) what is the relationship between fixations during the uncertainty alerts and crash frequency. Fixations were calculated based on a 200 ms threshold with a standard deviation of gaze position below 1°. Fixation location was based on five spatial areas of interest (AOIs) anchored by the road centre region, which was defined as the mode of gaze fixations that fell within a 6° circular region of the road centre area (See Percent Road Centre (PRC; Harbluk, Noy, and Eizenman, 2002; Victor, Harbluk, and Engström, 2005). The Top, Left, Bottom and Right regions of this AOI account for an equal division of the remainder of the road scene (for details see Louw et al., 2014).

5.3.1 Where do drivers look first?

Our results show that the OoTL manipulations influenced the AOI region first fixated by participants after the manipulations ceased (Figure 5.2). To assess how dispersed the groups' fixations were between the AOIs for each group and across all events, we calculated a dispersion index (D; Hammond, Householder, Castellan, 1970), defined as, "the ratio of the number of pairs in the data which are found to be different to the maximum number of such pairs, given the total number of observations" (Schafer, 1980). This produces a value from zero to one, where zero indicates the observations are concentrated in one category and one indicates the observations are distributed evenly among the categories:

$$D = \frac{(k(N^2 - \sum_{i=1}^{k} N_i^2)}{(N^2(k-1))} \tag{5.1}$$

Where k = the number of categories,
N = number of observations,
N_i = number of observations in the ith category.

Since some fixations coincided with the start of the uncertainty event, only those starting 200 ms after the cessation of the OoTL manipulations were analysed. In the Heavy Fog + Quiz and No Fog + n-back group fewer drivers fixated on the central region immediately after the screen was removed, and the dispersion index shows there was more variance in these groups compared to others. The high number of fixations on the top region for the No Fog + Quiz group is likely due to the location of the Quiz on the screen enveloping both the central and top regions. The high number of fixations on the top region for the No Fog + n-back was also expected, as drivers who are engaged in a non-visual cognitive task have been shown to have a higher vertical gaze angle compared to a baseline drive (Kountouriotis and Merat, 2016). Fixations between participants were least dispersed in the Light Fog and Heavy Fog condition, with the majority of first fixations located in the central region. These results suggest that, irrespective of screen visibility, performing a secondary task during automation caused more variation in drivers' first fixation, when they were required to re-engage in the driving task.

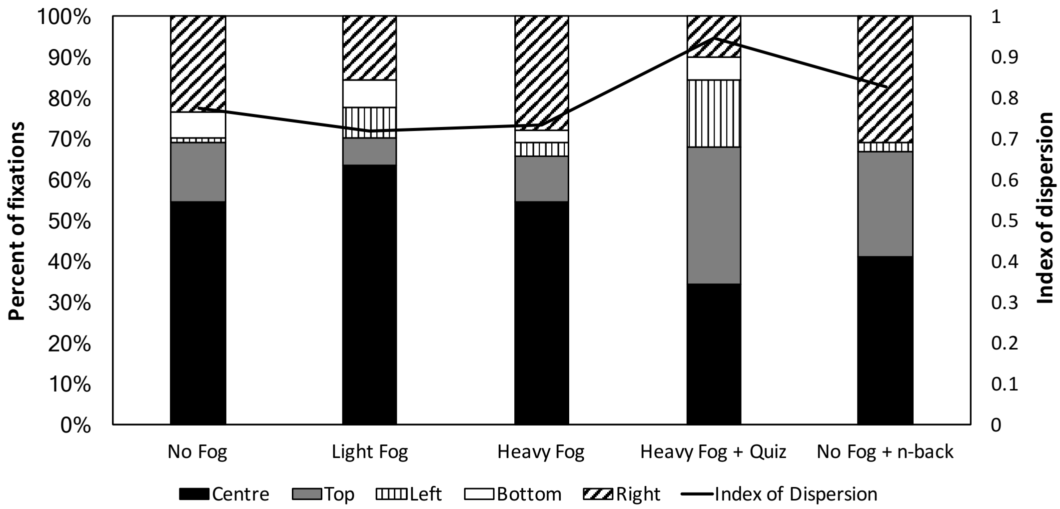
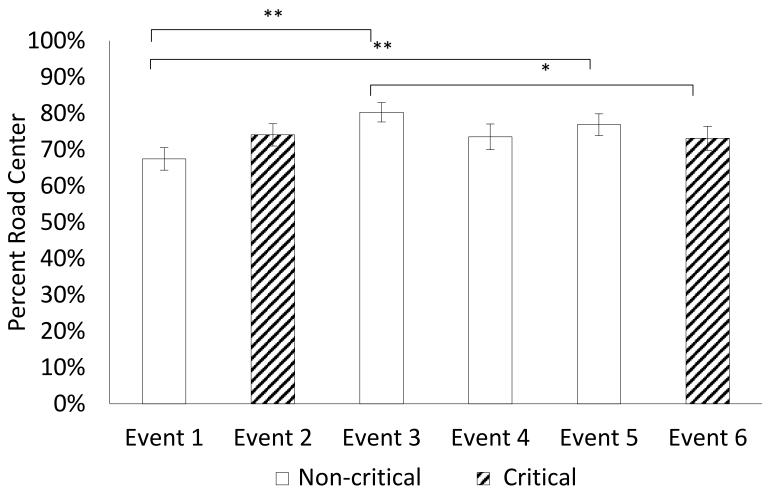


Figure 5.2: Location of participants' first fixation after the OoTL manipulations ceased, for all events.

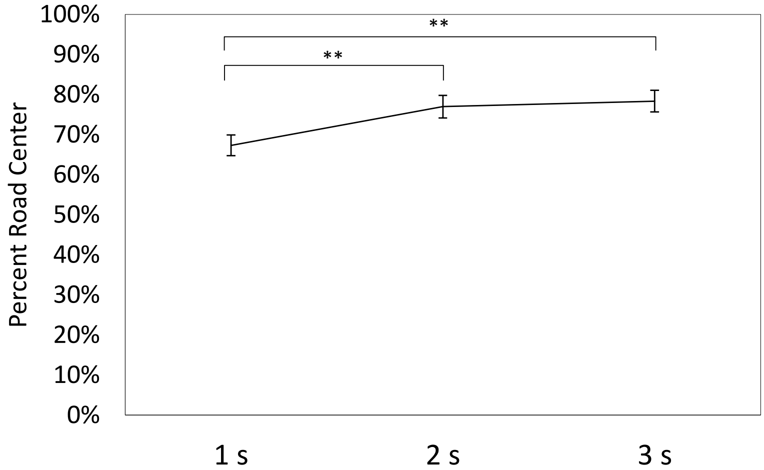
5.3.2 Effect of OoTL Manipulations on fixations

To understand how drivers distribute their visual attention while the automated system was in an 'uncertain' state, an index of PRC was calculated for three 1 s time windows, immediately after the OoTL manipulations ended. These were compared using a three-way ANOVA, with Event Number (1-6) and Time (1s-3s) as within-participant factors and OoTL Manipulation (5 Conditions) as between-participant factor.

Results showed an effect of Event Number ($F(5,350)=3.179$, $p<.01$, $\eta_p^2=.043$), where, as shown in Figure 5.3(a), drivers' visual attention distribution changed with successive events. Post-hoc comparisons revealed that PRC scores for Events 1 and 3 were significantly different. There was also an effect of Time ($F(2,140)=10.329$, $p<.001$, $\eta_p^2=.129$), and Figure 5.3(b) shows that PRC scores rose significantly from the first to the second and third second after the OoTL manipulations ended. There was an interaction of Event Number and Time ($F(10,700)=19.162$, $p<.01$, $\eta_p^2=.215$). However, post-hoc comparisons failed to show any meaningful patterns. Consistent with our previous results (Louw et al., 2015), there was no effect of OoTL Manipulation on fixations to the road centre in the first three seconds, however there was an interaction of Time and OoTL Manipulation ($F(8,140)=2.772$, $p<.05$, $\eta_p^2=.137$). To investigate this interaction, two-way ANOVAs were conducted for each of the three seconds, with OoTL Manipulation as between-participant factor and Event Number as within-participant factor. A main effect of OoTL Manipulation was observed only for the first second ($F(4,70)=2.997$, $p<.05$, $\eta_p^2=.146$). Post-hoc comparisons showed that during the first second, PRC scores were significantly lower in the Heavy Fog and Heavy Fog+Quiz group compared to the others. This indicates that drivers were scanning the environment more after not having seen the road beforehand, but at the expense of focusing on the lead vehicle.



(a) Six events



(b) First three seconds

Figure 5.3: Average Percent Road Centre frequency after the uncertainty alert, for (a) each of the six events, and (b) for the first three seconds after the uncertainty alert (right) * p<.05, ** p<.001.

5.3.3 Fixations in the Critical Events

The number of crashes in Critical Event 1 (CE1) and Critical Event 2 (CE2), did not differ significantly between the Conditions (CE1, p=.073; CE2, p=.064), as calculated by 2 chi-squared tests (Table 5.1). This suggests that crash propensity may not necessarily be linked to drivers' first point of fixation. To test for a relationship between fixations during the uncertainty alerts and crash frequency, PRC scores were calculated for six 1 s periods after the OoTL manipulations ceased. We compared PRC scores in CE1 using a two-way ANOVA, with Time Window (1s-6s) as within-participant factor and

Table 5.1: Crash counts out of 15 cases for Critical Event 1 (CE1) and Critical Event 2 (CE2) for each group in the automated drive.

	Critical Event 1		Critical Event 2	
	No Crash	**Crash**	**No Crash**	**Crash**
No Fog (N=15)	10	5	15	0
No Fog + n-back (N=15)	11	4	15	0
Light Fog (N=15)	14	1	14	1
Heavy Fog + Quiz (N=15)	13	2	15	0
Heavy Fog (N=15)	8	7	12	3
Total	**56**	**19**	**71**	**4**

Event Outcome (crash/no crash) as between-participant factor. We focused on CE1 as there were only four crashes in CE2. Not included in the analysis but important to note is that in the second before the OoTL manipulations ceased there was no difference in PRC scores between participants (Figure 5.4), therefore any changes in PRC can be attributed to drivers' strategies for coming back into the loop.

There was a significant effect of Time Window (F(5,325)=5.287, p<.01, η_p^2=.075), where post-hoc comparisons revealed significantly higher PRC scores in the third to sixth second, and immediately after the brake light, compared to that of the first second. There was no effect of Event Outcome (p=.526), however there was a significant interaction between Time Window and Event Outcome (F(5,325)=5.125, p<.01, η_p^2=.073), where PRC scores over time were clearly different for the event outcome groups (Figure 5.4). This is highlighted by results from independent sample t-tests comparing PRC scores between the Event Outcome groups for each of the six 1 s Time Windows. For the crash group, only 51% of total fixations in the first two seconds were on the road centre region, which compares to 70.5% and 84% in the same periods for those who did not crash, the latter being significantly different (t(73)=3.14, p<.01). However, in the third second, the crash group's PRC score rose to 97%, which was significantly higher compared to the no crash group at 71.3% (t(73)=2.238, p <.05).

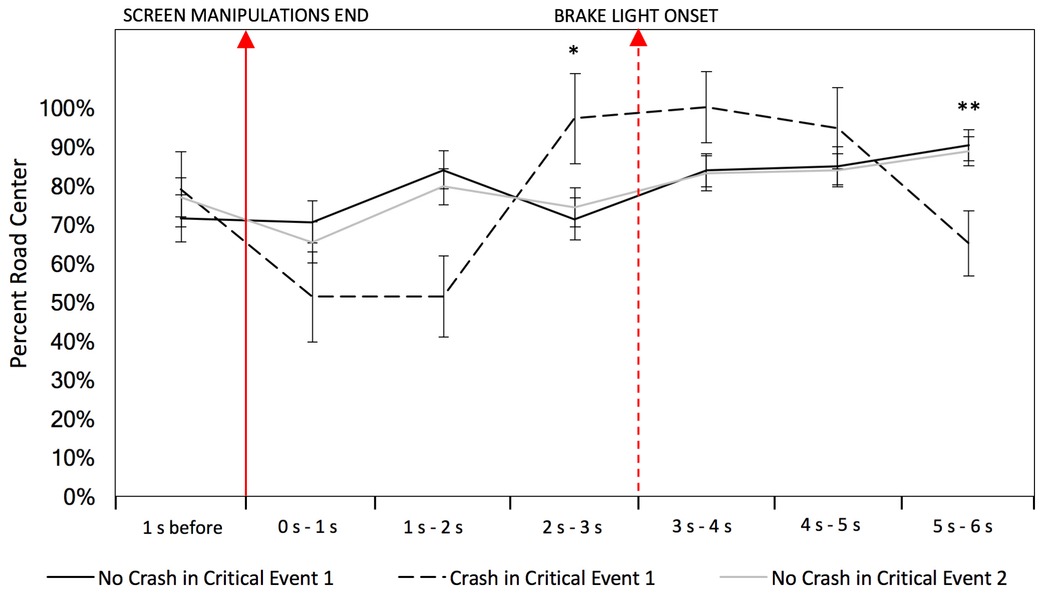


Figure 5.4: Percent Road Centre scores in Critical Event 1 for the crash (N=19) and no crash group (N=54) for seven 1 s time windows from the second before the OoTL manipulations ceased. Those who did not crash in Critical Event 2 (N=71) are also shown. *p<.05, **p<.01 (applies to comparisons for Critical Event 1).

In terms of preparation to respond to the hazard, it seems that drivers who crashed, left it too late. They maintained a high PRC score during the fourth and fifth second before dropping in the sixth possibly reflecting a late attempt at avoiding a crash. This was in contrast to the no crash group, whose PRC score rose gradually over the same period. Therefore, drivers with a more consistent frequency of eye fixations towards the point of the potential hazard (the road centre) and were more likely to avoid a crash than those who were late to fixate on the potential hazard. The PRC pattern for the crash group could be a result of these drivers either succumbing to an 'automation surprise' (Hollnagel and Woods, 2005) leading to increased cognitive demand (Engström, Johansson, and Ostlund, 2005), or over-trusting the system to handle the hazard (Lee and See, 2004), which led to them not feeling the need to distribute their attention in preparation for a response until it was too late. As a comparison, Figure 5.4 shows that the PRC trend for non-colliders in CE1 is remarkably similar to that of the 71 non-colliders in CE2.

5.4 Conclusions

The aim of this study was to investigate drivers' visual attention patterns during the resumption of manual control from PAD and whether these link to crash potential. Following Louw and Merat (2017), we hypothesised that drivers who crashed would have different patterns of visual attention towards the road centre, compared with those who did not. OoTL manipulations influenced drivers' first point of gaze fixation after they ceased, yet these differences resolved within 2 s, and there was also no association between OoTL manipulation and crash outcome. Key to bringing a driver back into the loop who then responds appropriately is directing their attention as early as possible towards the hazard that may lead to an automation disengagement. This avoids indecisive eye scanning and improves information acquisition and processing, which supports better decision-making and action execution (Parasuraman, Sheridan, and Wickens, 2000).

As vehicle automation evolves from SAE Level 2 to SAE Level 3, so the decisions that drivers will have to take regarding their involvement in the driving task will shift from being about when to intervene to whether to intervene. Considering that we do not have a well-defined understanding of drivers' competence to resume control safely, previous studies argued that drivers should remain engaged with the driving task during automation to intervene quickly if necessary. This justifiably conservative recommendation results in drivers not being relieved of the workload that automated driving promises, highlighting a familiar irony of automation (Bainbridge, 1983). This paper provides two recommendations that might help realise the potential for PAD to reduce workload: (1) automated driving systems needs to be able to direct drivers' attention towards the cause of a system limitation at least 6 s in advance of an adverse outcome and (2) drivers need to possess an accurate and confident understanding of their role and the capabilities of their PAD systems (Vlasic and Boudette, 2016). These are especially relevant for time-critical situations and where drivers are ultimately responsible for safety. A possible limitation of this study is that the automated drive duration used may not have been long enough to induce the out-of-the-loop states. Therefore, and with a view to developing a more complete understanding of drivers' capacity to resume control, a natural progression of this work is to investigate links between longer durations out of the loop, visual attention, takeover times, vehicle control and crash outcome.

What is already known on this subject

1. In the coming decades, the driving task will become increasingly automated. Irrespective of the level of automation, drivers will likely engage in non-driving-related tasks, which may impede their ability to avoid crashes if they are expected to resume manual control, should the vehicle reach a limitation.

2. Little is known about drivers' visual attention during such instances, yet this is especially important as automation renders traditional metrics of driver behaviour inadequate.

3. The design of safe automated driving systems can and should be informed by a clear understanding of how drivers' visual attention is distributed in the moments after they are expected to resume control.

What this study adds

1. This research improves and expands upon previous research by comparing how varying levels of drivers' awareness of, and engagement with, a partially automated driving system influences their visual attention distribution during critical and non-critical road events.

2. A detailed insight into drivers' eye fixation behaviour in these events is presented, and differences in visual attention patterns between those who crashed and those who did not is shown.

3. Our results suggest it is imperative that automated driving systems are able to direct drivers' attention no less than 6 s in advance to the cause of a manual take-over request, especially if this is a traffic threat that may lead to a crash. This is a conservative estimate, however, with the threshold likely to rise with increasing road and traffic complexity.

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Disclaimer The findings and conclusions in this report are those of the authors and do not necessarily represent the views of the European Commission.

Competing interests None declared.

Ethics approval University of Leeds Research Ethics Committee (Reference Number: LTTRAN-054).

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CHAPTER 6

COMING BACK INTO THE LOOP: DRIVERS' PERCEPTUAL-MOTOR PERFORMANCE IN CRITICAL EVENTS AFTER AUTOMATED DRIVING

ABSTRACT This driving simulator study, conducted as part of the EU AdaptIVe project, investigated drivers' performance in critical traffic events, during the resumption of control from an automated driving system. Prior to the critical events, using a between-participant design, 75 drivers were exposed to various screen manipulations that varied the amount of available visual information from the road environment and automation state, which aimed to take them progressively further 'out-of-the-loop' (OoTL). The current paper presents analysis of the timing, type, and rate of drivers' collision avoidance response, also investigating how these were influenced by the criticality of the unfolding situation. Results showed that the amount of visual information available to drivers during automation impacted on how quickly they resumed manual control, with less information associated with slower take-over times, however, this did not influence the timing of when drivers began a collision avoidance manoeuvre. Instead, the observed behaviour is in line with recent accounts emphasising the role of scenario kinematics in the timing of driver avoidance response. When considering collision incidents in particular, avoidance manoeuvres were initiated when the situation criticality exceeded an Inverse Time To Collision value of ≈ 0.3 s^{-1}. Our results suggest that take-over time and timing and quality of avoidance response appear to be largely independent, and while long take-over time did not predict collision outcome, kinematically late initiation of avoidance did. Hence, system design should focus on achieving kinematically early avoidance initiation,

rather than short take-over times.

6.1 Introduction

The advent of automated vehicles promises a number of benefits, including an increase in the flow and capacity of the road network (Kesting *et al.,* 2008, Ntousakis *et al.,* 2015), a wide range of economic benefits (Fagnant and Kockelman, 2015), an increase in shared mobility (Fagnant and Kockelman, 2015), and a reduction in energy consumption (Anderson *et al.,* 2014). Many of these forecasts have received a great deal of attention in recent years, including those predicting that vehicle automation will result in a reduction in road traffic accidents (Bertoncello and Wee, 2015).

The aim of partial (SAE, 2016; Level 2; L2) automated driving systems is to relieve drivers of the moment-to-moment demands of the control (lateral and longitudinal), yet not supervision, of the driving task. In conditional (SAE Level 3; L3) automated driving systems, drivers are able to relinquish both control and supervision of the driving task. However, drivers are still expected to be responsible for the safety of the vehicle when operating these systems, and should be available to resume manual control, should the system reach some limit, for example, due to poorly marked lane boundaries. During automated driving, drivers may shift their attention away from information relevant to the driving task, for example, the traffic environment or the status of the automated driving system, to one of a range of non-driving related activities (Carsten et al., 2012). This shift in attention potentially impairs drivers' ability to perceive, comprehend, and predict events in the road scene, diminishing their situation awareness (SA) (Endsley, 1995, De Winter et al., 2014). A key human factors concern regarding L2 and L3 systems is that drivers with deteriorated SA may be ill-prepared to regain the attention and motor-control necessary to safely navigate the vehicle, if a system limit is reached and manual intervention (or 'take-over') is required; an issue often referred to as the out-of-the-loop (OoTL) performance problem (Endsley and Kiris, 1995).

There is evidence to suggest that the non-driving related task drivers engage in during automation may affect how quickly and safely they can resume control (Gold et al., 2013; Zeeb et al., 2015; Radlmayr et al., 2014; Merat et al., 2014; Louw et al., 2015), though there is little consensus. For instance, Merat et al. (2012) compared drivers' responses to critical incident scenarios, while engaging in a verbal "20 Questions Task" (TQT). Compared to when drivers were not engaging in the TQT, the TQT had no effect on how long it took drivers to start the lane change, but it did affect their ability to quickly reduce the vehicle's speed to a safe level. In contrast, Neubauer et al. (2012) found that drivers engaging in a mobile phone conversation during a take-over, had shorter brake reaction times to a lead vehicle, compared to those who were not engaging in a mobile phone conversation. This lack of consensus is not surprising as studies have employed different experimental traffic scenarios (Naujoks et al., 2014, Radlmayr et al., 2014), with varying time-budgets (Gold et al., 2013; Damböck et al., 2012; van den Beukel and van der Voort, 2013), and human-machine interfaces (HMI), and in simulators of varying degrees of fidelity. As non-driving related tasks demand different levels of drivers' visual attention, it is important to compare the effect of a range of tasks.

In this study, conducted as part of the EU AdaptIVe project, we aimed to systematically take drives OoTL, by applying a number of screen manipulations that, to varying degrees, limited the amount of system and environmental information available to drivers during automation, before presenting critical and non-critical take-over events. During these events, instead of a 'take-over request', we used an 'uncertainty' alert, which required drivers to monitor the road scene and determine whether there was a need to resume control from automation. These manipulations were introduced by Louw et al. (2015, 2016) and Louw and Merat (2017), and are detailed further below. Previously, we showed that, during automated driving, drivers' eye-gaze concentration was differentially affected by the OoTL manipulations (Louw and Merat, 2017), as was the location of drivers' first eye-fixations in the road scene, after the manipulations ceased (Louw et al., 2016). However, these differences resolved within 2 s of the manipulations ceasing. While these studies have illustrated how vehicle automation affects drivers' visual attention when 'coming back into the loop', precisely whether and how the degree of visual information available to drivers during automation affects their perceptual-motor performance during the take-over is not clear, nor is what constitutes 'good' performance, in this context. This study aimed to investigate these issues.

A number of measures and metrics have been used to study drivers' performance in the take-over, including take-over time from automation (Damboöck et al., 2014; Gold et al., 2014), minimum Time To Collision (TTC; Gold et al., 2013, Louw et al., 2015), reaction time to an obstacle (Neubauer et al., 2012), minimum time headway to an obstacle (Merat and Jamson, 2009; Merat et al., 2014; Louw et al., 2015), and maximum accelerations during vehicle control in the transition (Zeeb et al., 2015; Hergeth et al., 2016). In particular, take-over time has been used most widely to judge driver performance during the resumption of control (for a review see Eriksson and Stanton, 2017). However, we have previously argued that take-over time may not be the most appropriate indicator of drivers' preparedness for, or appreciation of the unfolding situation (Louw et al., 2015), as drivers could simply be reacting to take-over requests (TOR) from the system. Indeed, as reported in studies on braking behaviours in manual driving, there exists a driver-related delay between initial brake application and full emergency braking (Ising et al., 2012; Hirose et al., 2008; Perron et al., 2001; Kiesewetter et al., 1999; Yoshida et al., 1998). Therefore, the current study analysed, not only drivers' take-over time, but also, the time it takes for them to react to a threat in the road environment.

There is also a need to understand whether, and how, automation affects the *quality* of drivers' vehicle control following a take-over, as drivers do not mitigate all risk just by resuming control or initiating a manoeuvre. While the quality of vehicle control can be described, in part, by vehicle-based measures, such as lateral acceleration or standard deviation of lane position (SDLP), their interpretation is often constrained to the particular scenario under investigation. To provide scenario-independent measures of vehicle control, and thus take-over quality, a possible solution is to analyse drivers' responses in relation to the kinematics of an unfolding situation. Inverse Time To Collision (invTTC), for example, is a measure that accounts for the visual looming effect of a braking lead vehicle (Lee, 1976; Summala et al., 1998; Groeger, 2000; Kiefer et al., 2003, 2005), and is an important crash risk indicator (Kondoh et al., 2008).

Victor et al. (2015) and Markkula et al. (2016) used this measure to show that a majority of drivers involved in naturalistic crash and near-crash scenarios during manual driving, reacted within 1 s of the kinematic urgency of the scenario, reaching values of invTTC $\approx 0.2\ \mathrm{s}^{-1}$, which suggests that the *timing* and *response rate* of drivers' initial response appears to be anchored to the criticality of the unfolding event. Based on their findings, Markkula et al. (2016) proposed that how drivers make use of and act on visual looming information from a lead vehicle in manual driving may also explain drivers' response processes when suddenly brought back into the control loop in automated driving. If not being in physical vehicle control due to automation causes a mismatch between drivers' internal model of a vehicle's dynamics and the actual vehicle dynamics (Macadam, 2003; Russell et al., 2016), then their ability to respond in manner that is appropriate for the criticality of the situation in hand may be impaired (cf. Fajen and Devaney, 2006; Fajen, 2008; Markkula et al., 2016).

The current study sought to evaluate this hypothesis, by analysing the timing and rate of drivers' responses (i.e. how fast they move brake pedal and steering wheel) in relation to the kinematics of the unfolding situation, and how this interacts with the degree of visual information available to drivers pre-take-over.

We hypothesised that drivers deprived of all visual information from the system and road environment would be furthest OoTL and, therefore, take-over control later and have the least consistent perceptual-motor control, than those who performed visual and non-visual tasks pre-take-over. However, drivers who had access to all visual information during automation were hypothesised to be the most in the loop and would, therefore, take-over control the earliest and have the most consistent perceptual-motor control during the transition.

6.2 Methods

6.2.1 Participants

Following ethical approval from the University of Leeds Research Ethics Committee (Reference Number: LTTRAN-054, seventy-five drivers (41 male), aged 21-69 years (M=36, SD=12) were recruited via the participant database of the University of Leeds Driving Simulator (UoLDS) and were reimbursed £20 for participation. Participants had normal or corrected-to-normal vision. Their average annual mileage was 8290 miles (SD=6723), and all participants had held a full driving licence for at least three years (M=16, SD=12) and drove at least twice a week.

6.2.2 Materials

The experiment was conducted in the fully motion-based UoLDS, which consists of a Jaguar S-type cab housed in a 4m spherical projection dome with a 300° field-of-view projection system. A v4.5 Seeing Machines faceLAB eye-tracker was used to record eye movements at 60Hz.

6.2.3 OoTL Manipulations

To vary the degree to which drivers had access to visual information from the system and road environment during automation, we applied one of five OoTL manipulation techniques, which have been described previously in Louw et al. (2015, 2016) and Louw and Merat (2017), but are repeated in Table 6.1 and shown in Figure 6.1. As outlined in Figure 6.1, it was anticipated that drivers in the No Fog conditions would be the most *in the loop* and drivers in the Heavy Fog + Task condition would the most *out of the loop* (See Table 6.1).

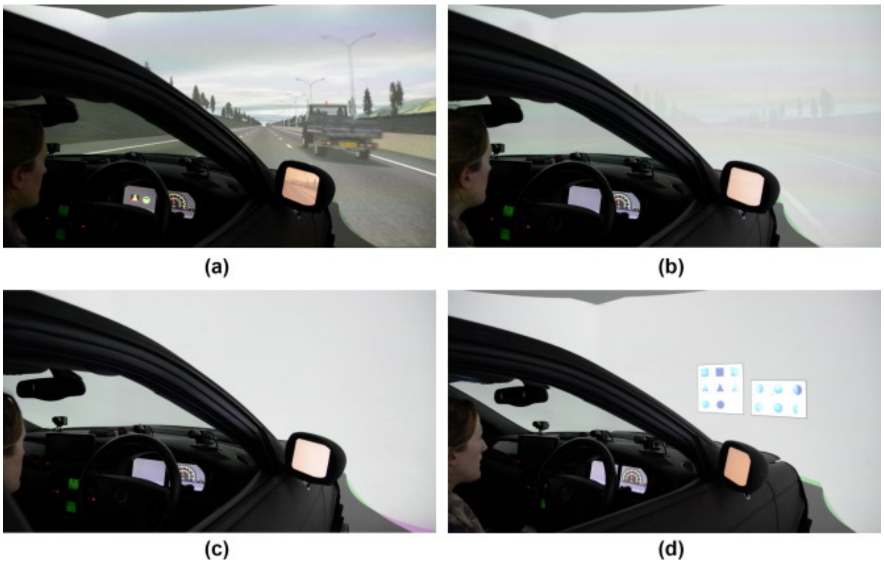

Figure 6.1: An example of drivers' view in the (a) no fog, no fog + n-back, (b) light fog, (c) heavy fog, and (d) heavy fog + task conditions..

6.2.4 Automated driving system

The automated driving system was only available when the vehicle was travelling between 65 and 75 mph in the centre of the middle lane. Drivers could engage the system by pressing a button on the steering wheel. When automation was engaged, and drivers' hands and feet were off the controls, automation could be disengaged by either pressing a button on the steering wheel, turning the steering wheel more than 2°, or depressing the brake pedal. If participants did not engage automation within 5 s of maintaining the vehicle position in the centre of the middle lane, the system

Table 6.1: Description of the OoTL conditions.

Condition	Description	Motivation/Aim
No Fog	The road scene was not manipulated in any way.	This served as a baseline condition, where drivers had access to all visual information from the system and road environment during automation.
No Fog + n-back	The road scene was not manipulated in any way, but participants completed the 1-back task (Mehler et al., 2011) during automation, where they heard a sequence of single digit numbers and were expected to repeat out loud the last number presented.	The aim was to simulate situations where drivers had access to all visual information from the system and road, but they were engaged in a non-visual task.
Light Fog	A translucent grey filter was superimposed on the road scene.	The aim was to give drivers the opportunity to perceive elements in the immediate vicinity of the road environment but not further afield, and to hinder their ability to accurately predict how road events might unfold in the future.
Heavy Fog	An opaque grey filter overlaid the road scene blocking all visual information from the road environment.	The aim was to simulate situations where drivers are completely looking away from the road scene and are unaware of the traffic conditions but not engaged in any other activity.
Heavy Fog + Task	An opaque grey filter overlaid the road scene blocking all visual information from the road environment. A visually presented secondary task was projected onto the front scene, which involved a series of web-based multiple-choice IQ test questions requiring verbal answers. Questions related to visuospatial shape-matching, general knowledge questions, and moderately challenging mathematics.	The aim was to simulate situations where drivers are not attending to visual information from the system or road environment, due to interaction with a visual secondary task.

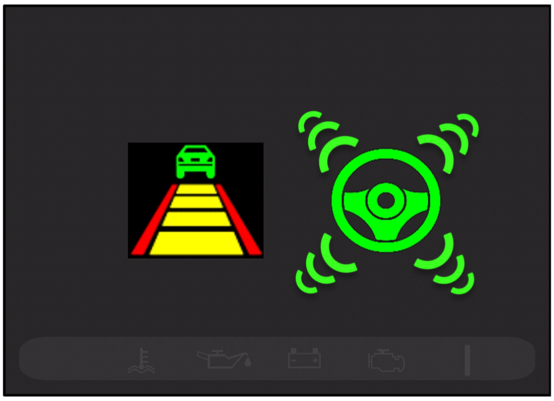

Figure 6.2: An example of the in-vehicle HMI with the Forward Collision Warning symbol on the left and the Automation Status Symbol on the right (flashing green in this example).

engaged automatically. Once engaged, the system assumed lateral and longitudinal control and adjusted the vehicle's speed to maintain 70 mph.

6.2.5 Human-machine interface

The human-machine interface (HMI) used for automation status related to the colour of a steering wheel symbol located in the vehicle's central display unit (Figure 6.2). This was solid grey when automation was unavailable, flashed green when available, and appeared solid green when active. For each event (see below), at the end of the OoTL manipulations, instead of a take-over request, drivers were presented with an 'uncertainty alert'. This was indicated by a flashing yellow symbol, which invited drivers to monitor the roadway and intervene, if they deemed necessary. If the driver deactivated the automation, the symbol appeared solid red for 2 s. Automation activation and deactivation were accompanied by an auditory tone (1000Hz, 0.2 s). A Forward Collision Warning (FCW) symbol included to the left of the automation status symbol gave drivers a visual estimate of the lead vehicle headway and a continuous alarm sounded if drivers reached an acceleration-based time-to-collision (TTC) of 2 s.

6.2.6 Experimental and Scenario Design

Five groups of 15 participants each were recruited for this study. All participants conducted an automated and manual (without the OoTL manipulations) drive, which were counterbalanced across participants. However, given the scope of this paper, only results of performance during the automated drive is included here. A 5 X 2 repeated measures mixed design was used, with OoTL Manipulation (No Fog, Light Fog, Heavy Fog, Heavy Fog+Quiz, No Fog+n-back) as a between-participant factor and Event Number (1-6) as a within-participant factor.

Each experimental drive lasted about 20 minutes and encompassed six discrete car-following events, within a free-flowing three-lane motorway, with ambient traffic. As shown in Figure 6.3, each drive contained two critical events (2,6) and four non-critical events (1,3,4,5). For all events, 7 s before the uncertainty alert, a vehicle entered the lane ahead, from the right. In the critical events, after 3 s of the OoTL manipulations ending, the lead vehicle decelerated at a rate of 5.0 m/s^2. This resulted in a collision if, after 3 s from the lead vehicle brake onset, there was no driver action. In the non-critical events, after 3 s of the OoTL manipulations ending, the lead vehicle either sped up or changed lane to the left, nullifying the event criticality.

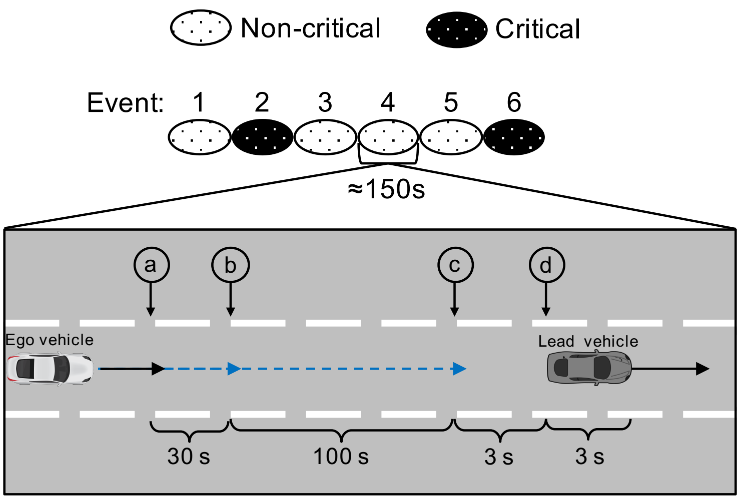

Figure 6.3: Schematic representation of each discrete event in the experimental drive. (a) to (d) represent various phases of the drive, where (a) denotes automation being engaged, (b) denotes the start of the OoTL manipulations, (c) denotes the end of the OoTL manipulations and the start of the uncertainty alert, and (d) denotes the start of the lead vehicle braking in the critical event.

6.2.7 Procedure

Upon arrival, participants read a hand-out which contained details of the experiment, but which did not include information on the critical situations. After signing the consent form, participants completed a 15-minute familiarisation drive, consisting of non-critical events only. This began with a short manual drive. Once familiar with the simulator controls, participants practised activating/deactivating the automation, were shown how the HMI communicated automation states, and experienced the OoTL manipulations. Participants then completed the experimental drive described in the previous section.

6.2.8 Analysis of drivers' perceptual-motor performance

Reaction time measures

Two metrics were adopted for quantifying timing measures during the take-over process: The *first* was take-over time ($t_{take-over}$), which was defined as a measure of the time between the end of the OoTL manipulations and a driver's disengagement of the automated driving system (by either pressing a button on a steering wheel, turning the steering wheel more than 2°, or depressing the brake pedal). We also computed action time (t_{action}), which was defined as the time from the end of the OoTL manipulation, to when the driver started a significant deceleration or steering action that was clearly intended to mitigate the impending crash.

During our studies, we have found that, in many cases, drivers touched the steering wheel but did not initiate an evasive steering action, and similarly, they often pressed the brake pedal but did not engage in an evasive braking action. Therefore, we looked for a clear steering or braking action and then searched for the starting point of this committed action. We developed a MATLAB (version R2015b, MathWorks) tool to allow the experimenter to judge when the driver committed to their response action. The following steps were taken to analyse t_{action} for the braking and steering responses:

1. The brake pedal signal and steering wheel signal were each filtered with a 1st order low-pass Butterworth filter, with a cut-off frequency of 0.05 Hz for braking, and 0.1 Hz for steering.

2. (a) For braking, the first local maximum brake pedal sample greater than 4 was identified (Red diamond marker in Figure 6.4). The brake pedal sample represented a unit-less value of brake effort, on a scale of 0 to 450.

   (b) For steering, the local maxima and minima values with an amplitude threshold of $\pm 2.5°$ were first identified, as per Schmidt et al. (2014). Then,

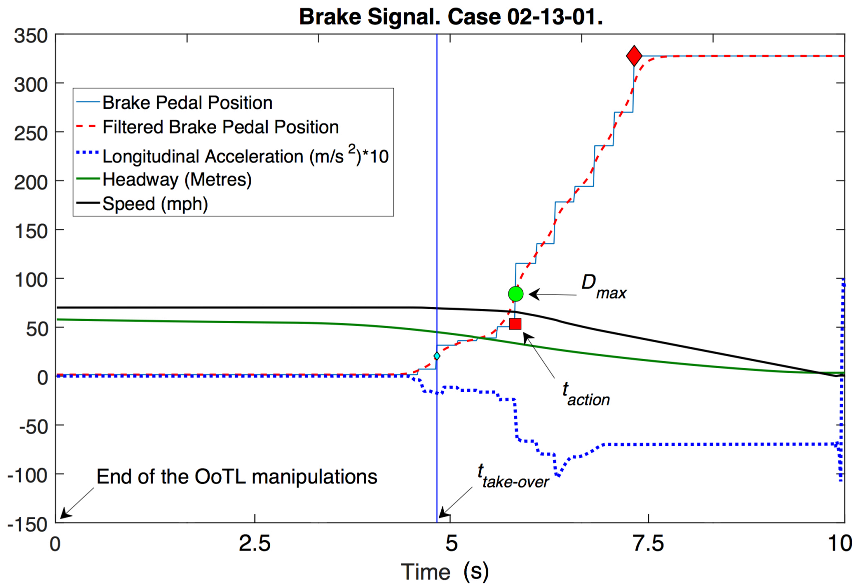

Figure 6.4: Example plot from the analysis of a brake signal, to determine t_{action}. Longitudinal acceleration values are multiplied by 10 for illustration purposes.

the global maximum steering wheel angle amplitude prior to the lane change manoeuvre was identified (Red diamond marker in Figure 6.5).

3. To identify the start point of the manoeuvre (t_{action}), two criteria were used. First, we identified the end of the plateau in brake or steering signal before the point identified above, such that there was less than a 0.0005 difference in values between consecutive samples (Red square markers in Figures 6.4 and 6.5). Second, to ensure accuracy, each start point was manually confirmed on a case-by-case basis, based on changes to the vehicle's speed and longitudinal acceleration, for braking, and the vehicle's offset and lateral acceleration, for steering. Minor adjustments to the location of the start points were made where necessary.

4. t_{action} was calculated as the time from the end of the OoTL screen manipulations (Figure 6.3) to the time corresponding to the start point identified in the previous step.

Vehicle control

To determine the quality of drivers' vehicle control after resuming control, we considered whether drivers were able to scale the rate of their collision avoidance response

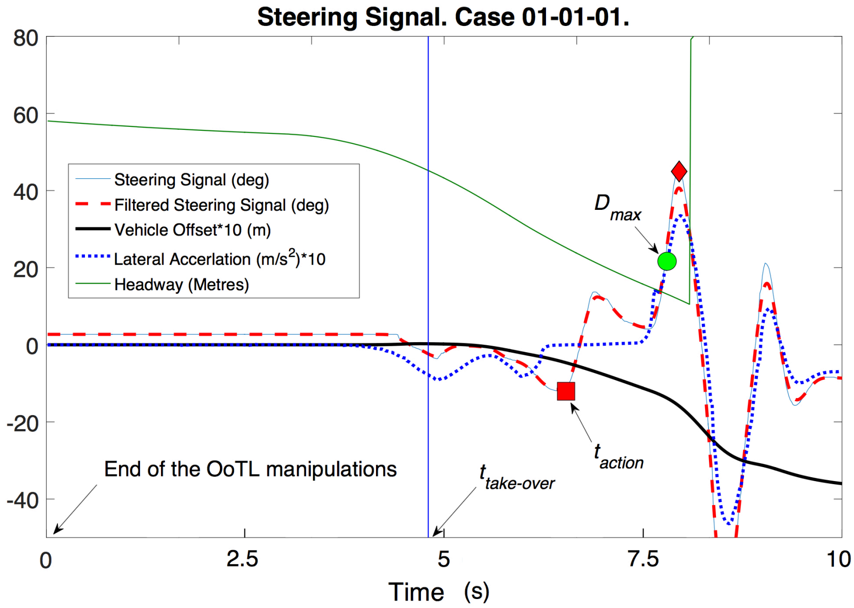

Figure 6.5: Example plot from the analysis of a steering signal, to determine t_{action}. Lateral acceleration and vehicle offset values are multiplied by 10 for illustration purposes.

to the event criticality. For this, we calculated and correlated two different measures.

The *first* measure was Inverse Time To Collision (invTTC; Kiefer et al., 2003, 2005) at t_{action}, and was used to quantify the criticality of the unfolding event at the point drivers began their collision avoidance manoeuvre. invTTC was calculated as relative speed divided by distance gap between the ego and lead vehicle, which takes the lead vehicle deceleration into account.

The *second* measure was the maximum derivative (D_{max}) of the control input that drivers used to avoid the collision, and was used to assess the rate and force of drivers' response to the critical event (Green circle marker in Figure 6.4 and Figure 6.5). D_{max} was taken from the time period between the response onset (t_{action}) and the maximum value of the respective control input. If drivers changed lane, then steering wheel angle was used, and if they braked, then brake pedal position was used. If drivers braked then steered, then steering wheel angle was used. For both steering avoidance (Markkula et al., 2014) and braking avoidance (Markkula et al., 2016), drivers scale the rate of their avoidance manoeuvre (i.e. D_{max}), to looming, as measured by invTTC. By correlating invTTC at t_{action} and D_{max}, we aimed to assess (i) whether similar situation-adaptive control behaviour would be present just after a take-over from automated driving, and if so, (ii) whether it would be affected by the OoTL manipulations. Specifically, as suggested in the Introduction, that drivers who had access to less visual information during automation, would generally have a more scattered correlation between invTTC at t_{action} and D_{max}.

As braking and steering inputs are measured in different units, they could not be analysed as a single data set, without first being transformed. To achieve this, separate regression equations were calculated for the steering and braking responses between invTTC and t_{action}. Next, the D_{max} values of the braking responses were transformed such that the intercept and slope of the regression equation was the same as that of the steering responses, allowing for the comparison of braking and steering responses.

Statistical analyses

The data were not normally distributed. Therefore, Kendall's non-parametric rank correlation test was used on the correlations throughout, which is preferred over Spearman's test, when using smaller sample sizes (Field, 2009). Kendall's *coefficient of determination* τ, was used here as a measure of goodness of fit. This was calculated using the *cor.test* R function in the 'MASS' package using the "kendall" method (Venables and Ripley, 2002). For illustration purposes, the approximate slopes and intercepts of the various factors were also calculated using robust linear regression, using the *rlm* R function in the 'MASS' package with default settings (Venables and Ripley, 2002). To test for an effect of the OoTL manipulations on $t_{take-over}$ and t_{action}, Kruskal-Wallis H tests were conducted using SPSS V.21 (IBM, Armonk, NY, USA).

Included in this study, based on 15 participants in each of the five OoTL manipulation groups and two critical events per participant, there were 150 transition cases considered for the analysis. However, twenty-six cases were excluded for various reasons. In 13 cases, drivers avoided a collision by changing lane but, at the point of automation disengagement, the initial steering wheel angle exceed $\pm 5°$ (which was possible because the steering wheel was not self-correcting) and there were no subsequent salient steering inputs. This indicated the lane change was due to a slow drift and the driver's intentional response could not be determined confidently. In 11 cases, drivers steered while braking hard and thus skidded such that steering had no effect. In 1 case, a driver did not respond at all, and in another the driver's response could not be determined using the method described above.

6.3 Results and Discussion

The results from this study will be presented with the aid of two types of graphs: the first graph relates to the timing of drivers' response and shows take-over time (x-axis, $t_{take-over}$) relative to action time (y-axis, t_{action}), for example as illustrated in Figure 6.6. If a data point falls on the dashed grey diagonal line, it indicates that the driver began a collision avoidance manoeuvre at the same time as they resumed control. The greater the distance along the y-axis between the data point and the dashed diagonal line, the longer the time between when drivers resumed control and initiated a manoeuvre. The red dashed lines on the x- and y-axes indicate the onset of the vehicle brake light. The second graph relates to vehicle control and shows D_{max} (y-axis) relative to invTTC at the start of drivers' response (x-axis), for example as presented in Figure 6.7. This figure attempts to demonstrate the rate of drivers' steering or braking input, during their collision avoidance manoeuvre, in relation to the kinematic urgency faced by drivers when they began their manoeuvre (i.e. the visual looming from the lead vehicle).

Results from a Kruskal-Wallis H test showed that, the lower the degree of visual information available to drivers during automation (from left to right in Figure 6.6), the slower they tended to take-over control ($\chi^2(4) = 9.820$, $p < 0.05$), with mean rank scores for $t_{take-over}$ shown in Table 6.2. However, there was no difference between the groups regarding when drivers began their collision avoidance manoeuvre (t_{action}, p = .784), which suggests that, the further OoTL drivers were, the higher the likelihood of a simultaneous take-over and manoeuvre initiation.

Figure 6.6 also shows that drivers who had access to all visual information pre-take-over (No Fog group), were most likely to resume control before the onset of the lead vehicle braking, suggesting more anticipatory responses. However, when drivers were either engaged in a non-driving related task and/or had some or all visual information withheld from them pre-take-over, they were more likely to resume control after the lead vehicle braked. These results suggest that the more OoTL drivers were, the more they reacted to external traffic than to system information, following the cessation of the OoTL manipulations.

Taking the situation kinematics into account, it is clear from Figure 6.7 that the lower the degree of visual information available to drivers, the more likely they were

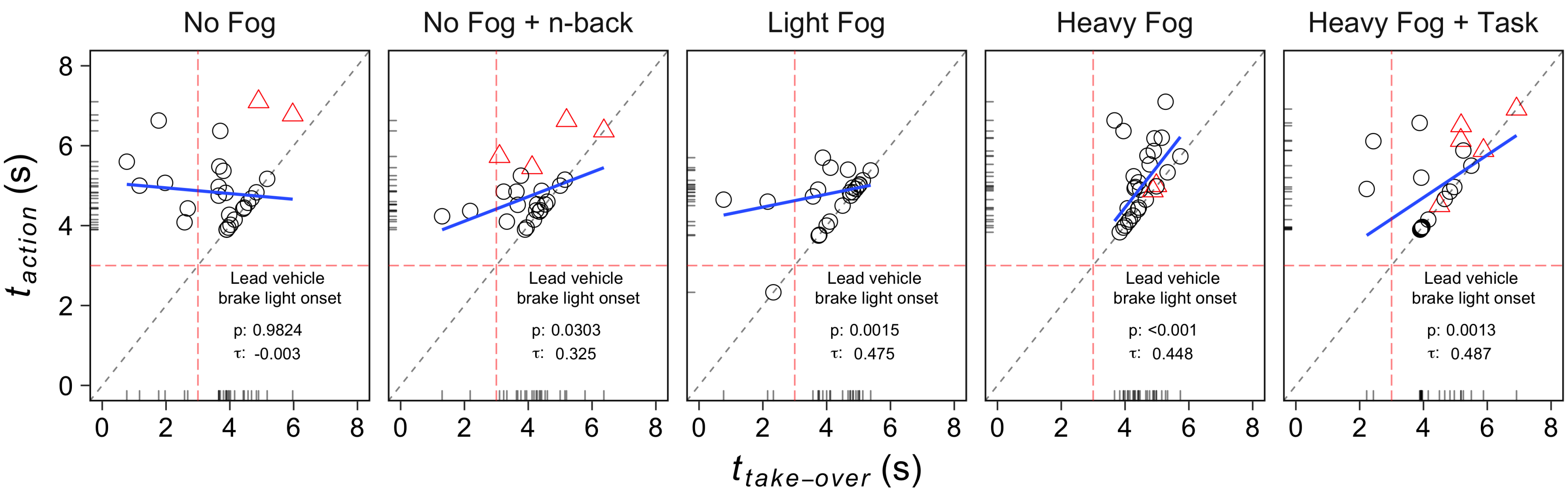

Figure 6.6: t_{action} relative to $t_{take-over}$ for the five OoTL conditions in both critical events. Red triangles show collisions and black circles show non-collisions. The blue lines are for illustration purposes only, showing the outcome of robust linear regression. Note how, from leftmost to rightmost panel, the general pattern is that cases group further to the right in the panel, indicating later $t_{take-over}$ for more OoTL drivers ($p < 0.05$) whereas the scatter in the vertical direction remains largely unchanged (no statistically significant effect of the OoTL manipulations).

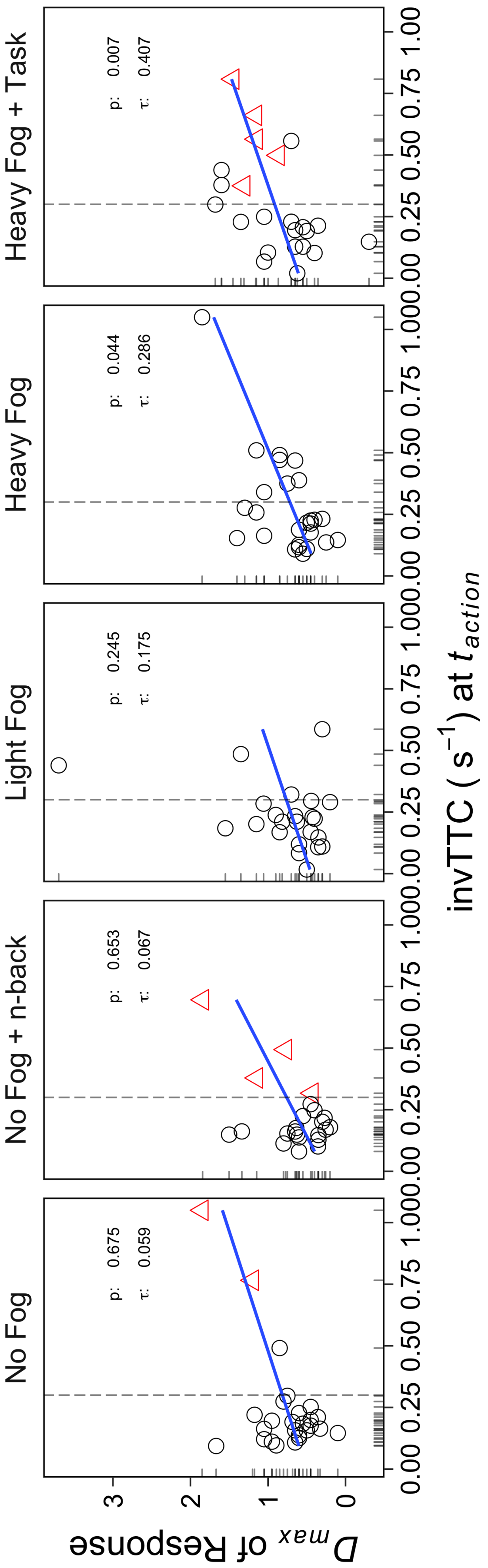

Figure 6.7: D_{max} of response relative to invTTC at t_{action} for the five OoTL conditions in both critical events. Triangles show collisions and circles show non-collisions. The blue lines are for illustration purposes only, showing the outcome of robust linear regression.

Table 6.2: Mean (SD) of take-over time and action time for the five OoTL conditions.

	No Fog	**No Fog + n-back**	**Light Fog**	**Heavy Fog + Task**	**Heavy Fog**
$t_{take-over}$ **(s)**	3.70 (1.22)	4.11 (1.07)	4.13 (1.11)	4.39 (1.03)	4.53 (.51)
Mean rank scores for $t_{take-over}$	46.31	63.96	58.23	68.11	75.39
t_{action} **(s)**	4.95 (0.91)	4.93 (0.99)	4.68 (0.72)	4.96 (1.02)	5.10 (.87)

to respond at invTTC of over 0.3 s^{-1}. It is also evident that the majority of drivers across the groups responded before the criticality of the situation reached a value of invTTC $\approx$ 0.3 s^{-1}. This is consistent with the findings of Victor et al. (2015) and Markkula et al. (2016), who showed that, during manual driving, drivers reacted within 1 s of the kinematic urgency of the scenario, reaching values of invTTC $\approx$ 0.2 s^{-1}. Overall, as the situation became increasingly critical, drivers scaled the rate of their avoidance response to the criticality of the situation, just as in manual driving, both for braking (Markkula et al., 2016) and steering (Markkula et al., 2014). Tau values shown in Figure 6.7 suggest that the rates of drivers' responses were less scattered the lower the degree of available visual information, which goes against our hypotheses. We proposed that Tau may be a good measure of scatter, however, considering the distribution of the data across the groups, Tau may not be the ideal measure, as it is sensitive to how much of the invTTC range is covered. Therefore, larger data sets with better coverage of the invTTC spectrum and/or more detailed analysis methods might clarify this further. Qualitative inspection of the plots in Figure 6.7 suggest that the general nature of the perceptual-motor scaling, in terms of slope and intercept, was rather similar between the OoTL manipulations.

For all cases that resulted in a collision, drivers began their avoidance manoeuvre when the situation criticality exceeded invTTC $\approx$ 0.3 s^{-1}. However, this cannot fully account for why drivers crashed in some cases, as in other cases drivers responded at the same criticality and avoided a collision. Further explanation can be derived from the type of response adopted by drivers after the take-over.

Results showed that, in the majority of cases, drivers mainly steered in response to the lead vehicle (68/124), while in 36/124 cases drivers mainly braked, and in 20/124 cases drivers braked then steered (Figure 6.8). This is consistent with findings of Gold et al. (2013) and Blommer et al. (2017), who also found that a high proportion of drivers steered in crash-imminent situations, following a take-over, despite the fact that previous studies have shown braking to be the more common response in manual driving (Adams, 1994). Figure 6.9 shows that drivers who braked after the situation criticality reached invTTC ≈ 0.3 s^{-1}, were unable to avoid a collision, despite clearly scaling the rate of their brake response to the higher criticality of the situation. This is not surprising, as it is a well known aspect of road vehicle dynamics that steering collision avoidance remains a feasible option for a longer time than braking avoidance, during the run-up to a potential collision (Rice and Dell'Amico, 1974; Lechner and Malaterre, 2015).

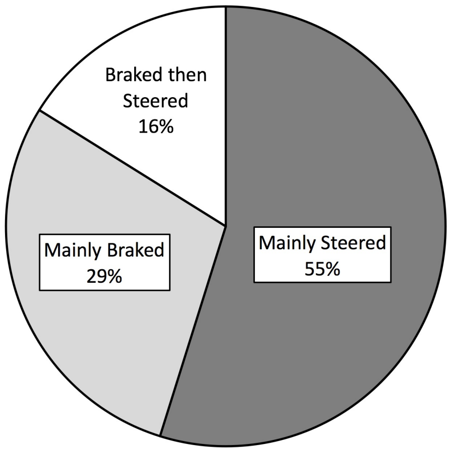

Figure 6.8: Combined frequency of drivers' responses in CE1 and CE2.

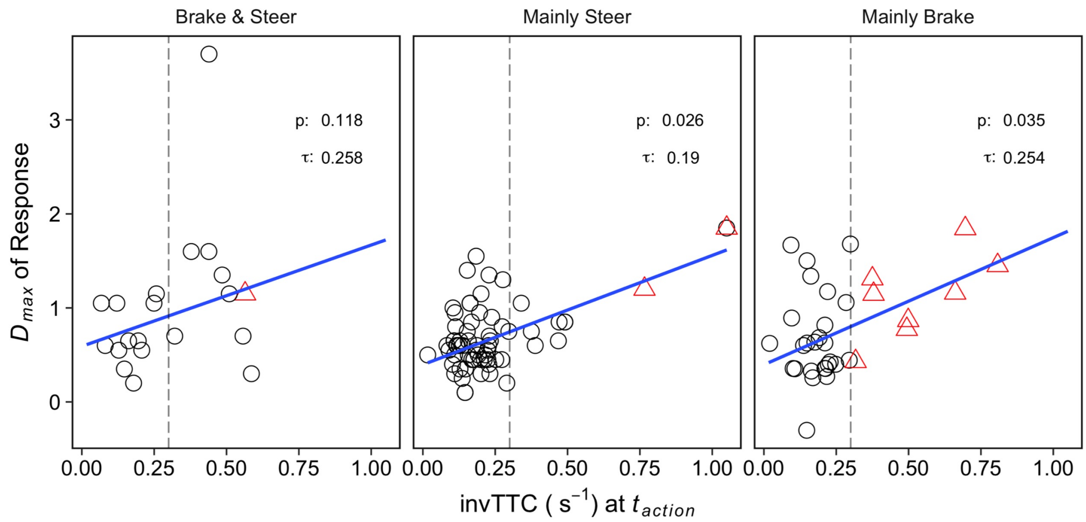

Figure 6.9: D_{max} of response relative to invTTC at t_{action} for the three response categories. Triangles show collisions and circles show non-collisions. The blue lines are for illustration purposes only, showing the outcome of robust linear regression.

In terms of actual number of collisions with the lead vehicle, Figure 6.10 shows that all collisions occurred in Critical Event 1 (CE1). While there were five cases in Critical Event 2 (CE2) where drivers responded after the criticality reached invTTC $\approx$ 0.3 s^{-1}, it is likely that the previous exposure might have helped these drivers make the correct decision to apply steering. In none of the cases that resulted in collisions, did drivers resume control or initiate a response before the onset of the lead vehicle braking, which could indicate increased decision-making time to take-over control. However, in 14 of the 108 non-collision, drivers resumed control (13 cases) or initiated a response (1 case) before the onset of the lead vehicle braking, which could indicate more anticipatory responses. Finally, Figure 6.10 shows that regressions were similar between the CE1 and CE2, which suggests that drivers' motor-control was largely unaffected by whether they had previously experienced a critical event.

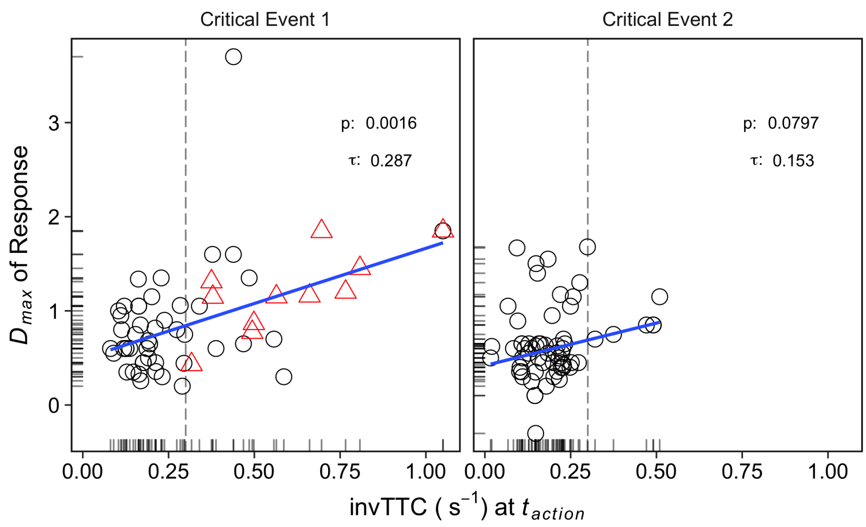

Figure 6.10: D_{max} of response relative to invTTC at t_{action} for Critical Event 1 and Critical Event 2. Triangles show collisions and circles show non-collisions. The blue lines are for illustration purposes only, showing the outcome of robust linear regression.

6.4 Conclusions

The analyses presented here provide some novel insights into the importance of visual information for drivers' perceptual-motor performance in critical situations during the resumption of control from automation.

Previously, we reported that the OoTL manipulations influenced the location of drivers' first eye-fixations after the manipulations ended, but that the effects resolved within 2 s (Louw et al., 2016). However, it was not clear whether the effect of the manipulations ended there or if they had an effect on drivers' perceptual-motor control. One important finding from this study is that, despite there being no differences regarding where drivers directed their visual attention, the less visual information available to drivers during automation, the later they took over control.

We hypothesised that the more OoTL drivers were, the less consistent their perceptual-motor performance. However, there was no difference between the groups regarding how long it took drivers to begin a collision avoidance manoeuvre, or, indeed, whether they would experience a collision. In addition, the subsequent kinematic analysis showed that the degree of visual information available to drivers pre-take-over did not influence whether and how drivers scaled the rate of their response to the situation criticality, at least not in any way that could be detected with the present data and analyses. This suggests that the level of drivers' situation awareness during automation has an impact on the timing of their take-over ($t_{take-over}$), but not necessarily on when they began a collision avoidance manoeuvre (t_{action}) or the quality of their subsequent vehicle control (D_{max}). This brings into question the usefulness of take-over time as a measure of 'good' performance in the take-over.

Another finding is that the majority of drivers responded below invTTC ≈ 0.3 s^{-1}, which was common for cases that avoided a collision, while all cases that resulted in a collision shared the following characteristics: *First*, for all collisions, drivers began their evasive manoeuvre when the situation criticality was above invTTC ≈ 0.3 s^{-1}. *Second*, drivers who crashed braked instead of steering, or braking then steering. *Third*, all collisions occurred in the first critical event, which is in line with previous findings that drivers' familiarisation with the event and experience with the system, results in fewer interaction errors, and safer outcomes (Engström et al., 2010; Lee et al., 2002; Benderius et al., 2014).

Taken together, our results suggest that it is important that, following a take-over, drivers act on any threat as early as possible in the kinematic scenario. While in the current study the usefulness of take-over time has been questioned, situations giving rise to take-over event will likely vary widely, and what is important is that drivers are able respond to system feedback in a timely manner. Therefore, the fact that the OoTL manipulations influenced how quickly drivers disengaged the automated driving systems has important HMI design implications for automated vehicles. For instance, HMIs that emphasise situation-relevant information before the take-over may facilitate safer take-over situations. With increasing situation criticality, drivers clearly attempted to adjust the rate of their collision avoidance response. Despite this, in many cases drivers were unsuccessful at avoiding a collision. This indicates that, should a system-initiated take-over be required, automated driving systems must support drivers during the transfer of physical vehicle control, by providing either advanced warning or vehicle control that reduces the situation criticality, via, for example, haptic shared control, Collision Mitigation by Braking (CMbB) or Emergency Steer Assist (ESA). A supportive HMI could also encourage drivers who respond late in the kinematic scenario to apply steering avoidance (the situation permitting, such as the one under investigation here).

The current study sets out some avenues for future work. For example, the scattered gaze-fixations of colliders (Louw et al., 2016), possibly contributed to their braking response starting late in the situation kinematics, and further work is required to ratify this link, which, if found to be true, strengthens the argument for an HMI that is able to direct drivers' attention to relevant information. Furthermore, what constitutes '*quality*' regarding driver performance in the transition will vary according to the level of responsibility being transferred as well as the road traffic situation itself, which motivates the need to evaluate a range of real-world take-over scenarios.

Finally, it is important to understand further how automation impacts on the kinematic-dependencies of driver responses to critical events, as recent work by Blommer et al. (2017) has shown that avoidance responses come later after a transition out of automated driving than in manual driving. It remains an open question whether or not drivers' scaling of avoidance responses to kinematics also change between manual and automated modes of driving.

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CHAPTER 7

FINAL DISCUSSION AND CONCLUSIONS

7.1 Final Discussion

This research was conducted as part of the Human Factors sub-project of the **AdaptIVe** (**A**utomated **d**riving **ap**plications and **t**echnologies for **I**ntelligent **Ve**hicles) project, co-funded by the European Union, under the 7th Framework Programme (AdaptIVe Project, 2014). The overall goal of the AdaptIVe project was to develop various automated driving functions for daily traffic, by dynamically adapting the level of automation, to the situation and driver status.

The specific objective of the Human Factors sub-project was to develop high-level use cases for test and development throughout the project and collect research issues on the interaction of drivers with automated vehicles, that currently remain unresolved. A further objective was to conduct experiments in different laboratory settings, including dynamic driving simulators, and, if suitable, also instrumented test vehicles, and based on the evaluated results create functional requirements and decision strategies for collaboration between the human driver and the automated driving system, in particular situations.

Thus, the focus of this thesis was on the assessment of the effect of vehicle automation on the human driver and not of the technology underlying the automation. The studies in this thesis were not designed to propose and evaluate prototypical automated driving systems or human-machine interfaces (HMI) nor reflect precise real-world use-cases.

The design of the experimental work was guided, on the one hand, by the desire to answer practical questions that arose from the literature regarding how drivers interact with an automated driving system, and, on the other hand, the desire to better understand the physical and cognitive/attentional aspects underlying the human out-of-the-loop problem. The results obtained have allowed us to draw practical conclusions regarding the effect of automation on driver behaviour, but also, more fundamentally about the nature of the driver out-of-the-loop phenomenon in the context of highly automated driving.

7.2 Review of experimental investigations

Five specific research questions were posed for investigation in Chapter 1, and the series of papers reported in this thesis and discussed below have addressed these.

1. How does automation affect drivers' performance in transition situations, requiring control- and tactical-level responses?

2. How does automation affect drivers' behaviour in automation, compared to manual driving?

The literature on transitions in automated driving is dominated by experiments assessing driver behaviour in scenarios requiring only control-level responses, i.e. maintaining lane position, while relatively little has been conducted on how drivers can handle scenarios that represent tactical and strategic levels of driving, as per Michon (1985). This gap acted as the starting point to this research.

One of the challenges of comparing performance across control- and tactical-level driving scenarios is that the dynamics of the scenarios (also referred to as 'kinematics' in the literature) themselves are often dissimilar, for example, maintaining lane position compared to deciding whether to brake or change lane to avoid a collision. Therefore, it is hard to ascertain whether changes in driving performance are due to differences in road and traffic layout, or drivers' ability to navigate them. The study presented in Chapter 2 overcame this shortfall by examining the effect of scenarios requiring both control-level and tactical-level responses on driver behaviour, by introducing different rule-based instructions for how to respond to the same situation (stationary lead vehicle) during a transition. A secondary aim of this study was to assess whether any observed differences were due to either the physical or attentional aspects of not being in control as a result of automation. Therefore, the experiment also required drivers to either maintain visual attention towards the road centre throughout the experimental drive, or to read from an iPad to the side of the steering wheel while automated driving was active, and before requests for resumption of control.

Overall, findings showed that drivers experiencing automation in two conditions (no distractions and distracted by reading task) performed worse when avoiding a collision, compared to a manual condition, which was in line with previous findings (Young and Stanton, 2007; Merat and Jamson, 2009; Merat et al., 2012). However, the short (1-minute) periods of automation used in this study did not impede drivers' ability to complete simple operational and tactical-level driving tasks, following a system-initiated take-over request. That there were differences between the manual drive and both automation drives, but not between the automation conditions themselves, led to the hypothesis that the OoTL phenomenon encompasses a strong element of physical control, with the effects of attention possibly a more subtle aspect. However, the possible priming of the repeated-measures design suggests that any observed effects of being out of the cognitive control loop were conservative. Therefore, the particular contribution of the attentional aspect of the OoTL problem remained unclear, and this provided impetus for the study presented in Chapter 3.

Chapter 3 investigated the attentional dimensions of the OoTL problem in the transition. To achieve this, I artificially induced two driver OoTL states, by manipulating the degree of visual information available to drivers during automation, both regarding the dashboard displays in the vehicle and also the road environment. Based on Endlsey's (1995) definition of Situation Awareness (SA) and Kienle et al.'s (2009) definition of an OoTL driver, I hypothesised that, by restricting drivers' access to system and environmental information during automation, and before an automation uncertainty event, drivers would have a reduced ability to recognise and respond to a critical scenario. In two conditions, drivers either had access to no system or environmental information during automation (Heavy Fog condition), or only limited visibility of environmental information (Light Fog condition), which was hypothesised to take drivers OoTL, and help us understand whether the information drivers had access to during automation would change how they interacted with automation during and after the transition. To detect whether drivers were only taking back control in response to a take-over request, or responding to some system or environmental cue, I introduced an 'uncertainty alert' in place of the more common 'take-over request'. This *invited* drivers to monitor the road rather than *instructed* them to resume control.

The results on vehicle control in Chapter 3 corroborated and extended those presented in Chapter 2, showing that drivers' response profile to a potential collision scenario was less controlled and resulted in more collisions in the critical events, compared to when they were in manual control. However, there were no differences between the two OoTL manipulation groups, which implied either that the amount of visual information available to drivers was not as important as being in physical control, that the methodology was not appropriate, or that the vehicle-based measures, or analysis thereof, used to test this hypothesis were robust to any underlying differences. This is discussed further in Section 7.4. Yet, crash outcomes provided some indication that, by withholding driving-relevant information, using the OoTL manipulations, I was at least successful at taking drivers out-of-the-loop *during* automation, because the Heavy Fog condition resulted in significantly more collisions than the Light Fog condition, which, in turn, resulted in more collisions than the Manual condition. Results also showed that, with repeated exposure to the transition events, drivers became less engaged in the driving task once automation was re-activated. However, this left questions about the effect of non-driving related tasks, both visual and cognitive, and whether these would support or augment drivers' ability to safely resume manual control. These concerns motivated the focus for papers presented in Chapters 4-6.

3. What is the pattern of drivers' visual attention distribution during automation?

In Chapter 4, additional OoTL screen manipulation conditions were added, including one which had no manipulations and one which removed all system and environmental information as well as presenting drivers with a visual task. Driver gaze dispersion in each condition was assessed, to determine what information from the system and road environment drivers attend to during automated driving, given the limits imposed on them by the OoTL manipulations.

Results showed that, during automation, drivers' horizontal gaze was more dispersed than during manual driving, which is in line with findings of Carsten et al. (2012) and Damböck et al. (2013). Both horizontal and vertical gaze dispersion were differentially affected by the OoTL manipulations, while they were active. However, while these short 3 minute periods of OoTL manipulations seemed to have a noticeable effect on drivers' visual attention allocation, they did not appear to have a long-lasting effect once they ceased, at least regarding gaze dispersion. However, quite how quickly these differences subsided was unclear, and I concluded by tentatively proposing that any information presented to drivers during automation should be placed near the centre of the road scene and that other measures should be used to evaluate other possible differences. The papers presented in subsequent chapters aimed to assess this hypothesis by analysing the distribution of drivers' fixations in the transition, as well their perceptual-motor performance upon the resumption of manual control.

4. How does automation affect drivers' visual attention distribution during and immediately after the transition?

Chapter 6 showed the OoTL manipulations influenced drivers' first point of gaze fixation after they were asked to attend to an evolving event. Differences resolved within one second, and visual attention allocation adapted with repeated events, yet the crash outcome was not different between OoTL manipulation groups. Interestingly, drivers who crashed in the first critical event had a lower number of eye fixations towards the road centre before brake light onset and a higher number following brake light onset. However, those who did not crash demonstrated a more stable pattern, fixating towards the road centre early on in the unfolding event, and sampling it consistently as the situation unfolded. These findings led to the recommendation that automated vehicle systems should warn drivers no less than 6 s before reaching a system limit and that drivers should be aware that looking away from the road centre for too long could be dangerous in Level 2 automated driving systems. The remaining questions were whether the effect of the OoTL manipulations would manifest as differences in vehicle control, and how best one might define and measure 'safe' performance in the transition. For this, a kinematics-dependent analysis of drivers' perceptual-motor performance (i.e. the timing and magnitude of drivers' responses) during approach to the two critical events, in automation was conducted.

5. How does automation affect drivers' perceptual-motor performance in the transition?

Results in Chapter 6 indicated that the less visual information is available to drivers during automation the longer their take-over time, but this did not predict collision outcome, which was instead predicted by kinematically late initiation of avoidance manoeuvring. Furthermore, results suggested that take-over time and the timing and quality of avoidance appear to be largely independent phenomena and that kinematically early avoidance response may be more important for safety than short take-over times. These findings have clear implications for the design and placement of in-vehicle infotainment systems in highly automated vehicles. Systems potentially obstructing drivers' view of unfolding events or important driving-related information may negatively influence their ability to react promptly. These results offer suggestive evidence that heads-up display (HUD) type interfaces should be avoided in Level 2 systems.

In summary, it is clear that the OoTL manipulations affected drivers' eye gaze dispersion during automation, as well as the uniformity of the location of drivers' first fixations once the manipulations ended. However, within three seconds of the manipulations ending, while drivers' were evaluating the state of the environment and automated driving system, the differences between the conditions resolved, and in many cases, this was before drivers resumed control. Interestingly, differences between the OoTL manipulations emerged once again regarding the timing of drivers' initial response (take-over time). There was a significant difference in how long drivers in the different conditions took to resume control, though there was no difference in the quality of the subsequent vehicle control. Therefore, the OoTL manipulations appeared to have some effect on when drivers chose to intervene, even while there were no differences in the allocation of their visual attention. Clearly, this disconnect between drivers' visual attention and their perceptual-motor performance requires more detailed investigation. HAD systems should, therefore, afford drivers additional time and/or vehicle control support (e.g. haptic shared control) based on how disengaged they were from the driving task, in the lead up to a take-over request. This suggests that being in the loop or out of the loop cannot simply be a binary distinction. Of course, there may be instances where drivers are fully in the loop or fully OoTL, but in most cases, they will find themselves somewhere in between, and where along that continuum will depend on a combination of factors, which are discussed in more detail in Section 7.4.

The relative contributions of the above results on driver performance in the transition are still unclear, but Section 7.4 lays a basis for future experiments to investigate this further. What follows is a discussion of the merits of the methodologies and analyses used in these studies.

7.3 Reflection on methodology and measures

Methodology used

A key limitation of the study presented in Chapter 2 was that drivers were perhaps over-exposed to critical incidents, resulting in a learning effect and reducing the power of following scenarios. While this shortcoming was addressed during the design of the studies presented in Chapters 3-6, it could not be removed altogether. For instance, only 25% of those cases in the automated drive resulting in a collision experienced the manual drive first.

The screen methodologies used in Chapters 3-6 presented a novel means of inducing the OoTL state and studying its effects on driver behaviour. However, it is important to reflect on questions around its usefulness and validity. The first is whether the manipulations were successful in taking drivers OoTL. Initial results presented in Chapter 3, regarding glance behaviour to the HMI during automation, provided some encouraging results about how engaged drivers were with the driving task during automation, and as a consequence of the manipulations. These manipulations were expanded in Chapter 4 and Chapter 6, and their effects on gaze behaviour and gaze fixations were clear. For instance, Chapter 4 showed the manipulations had a differential effect on gaze dispersion during automation, and Chapter 6 revealed the manipulations influenced the location of drivers' first fixation during the transition, but also that these differences resolved within 2 s. After the resolution of these differences, there was no substantial effect of the manipulations on visual attention allocation or vehicle-based measures.

One explanation is that the OoTL manipulations themselves were not strong enough, regarding the duration of exposure, to have any significant lingering behavioural effects on physical control. An alternative explanation is that the manipulations were successful, but that the measures used to assess perceptual-motor performance in the transition may not have captured any underlying differences. However, it may also be that the recovery period (time between the uncertainty alert and the brake light onset) was sufficient for drivers to recover SA, and so the effects of the manipulations did not manifest as deficiencies in manual control.

A reviewer for the paper presented in Chapter 3, argued that using fog-like manipulations do not practically represent an OoTL condition during real automated driving conditions, as the typical OoTL state is more of a volunteer behaviour (e.g., distraction), while the fog conditions are more of a forced behaviour (i.e., information is blocked). The reviewer went on to suggest that these two behaviour styles may result in different focus points for drivers' attention. It is important to note that the OoTL manipulations were never intended to represent real-world settings. While voluntary disengagement may exacerbate the OoTL state, the core factor contributing to the development of the state itself is feedback, as argued by Endsley and Kiris, (1995), Kienle et al. (2009), and Norman (1990). Therefore, whether feedback is limited voluntarily or involuntarily, the end result will be similar. That the manipulations cause limited feedback involuntarily, and that voluntary disengagement cannot be controlled suggests that our data only underestimate the possible real-world effects.

Eye-tracking measures

A large proportion of the work conducted for this thesis involved the analysis of drivers' eye movements (e.g. Gold et al., 2013; Zeeb et al., 2015), and the faceLAB eye-tracker used was not without its limitations.

The faceLAB eye-tracker uses a combination of image processing techniques in conjunction with infra-red reflection on the iris, to localise the pupil of the user and calculate the gaze focus point. The quality of the eye gaze data point being collected (at 60 Hz) is graded based on the quality of the information available to the system. While the faceLAB always endeavours to achieve the highest possible gaze quality level, there are times where the tracking confidence is degraded, and gaze estimates can only be extracted using video or, in the worst-case scenario, head position. Given the importance of precision in my analysis, only data with the highest gaze quality level was used. However, in some cases, this meant that if a particular driver's eye-tracking data were poor quality, then they would be under-represented in the dataset. Moreover, while this is a pragmatic approach to ensuring that only high-quality eye-tracking data is used, the resulting analysis does not account for the missing data and is therefore also at risk of over-representing the reported data. A more transparent approach would have been to report the proportion of eye-tracking data that was excluded from the analysis.

A further limitation of the system is that the faceLAB eye-tracker does not contain a world-map of the driving scene, which made it difficult to assess the exact point of drivers' fixations in the environment. Therefore, the PRC technique was used to evaluate the general allocation of drivers' visual attention. In particular, the central region of the areas of interest was used because that was the general location of the lead vehicle. While this proved useful in separating colliders and non-colliders in Chapter 5, there are still some concerns over the accuracy of this analysis method, particularly since not containing a world map means that is it difficult to link gaze points to moving objects. The 6° circular radius used, enveloped the rear-end of the lead vehicle at the start of the uncertainty alert. However, as the lead vehicle braked it would have expanded in the forward visual field, which meant that, at some point, the circular region would not have captured the entirety of the rear of the lead vehicle. Moreover, using the central region may have been more or less accurate depending drivers' deceleration rate and collision avoidance manoeuvre (brake or change lane). Given the limitations of the faceLAB system, and the method of analysis used as a compromise to these, a more accurate approach to determining whether drivers were fixating on the lead vehicle may have been to adjust the radius of the central region according to the size of the of lead vehicle (based on distance headway) in relation to drivers' position. Also, the time windows used could have been adjusted to only include the period when the driver was in the middle lane.

As mentioned in previous chapters, the mapping of the areas of interest onto the road scene was achieved by calculating the position of the central region, for each participant. The middle of the central region was anchored to the x y coordinates of the mode of each driver's fixations (based on a 200 ms threshold with a standard deviation of gaze position below 1°) during a 90 s period of manual driving on a straight road. In the PRC technique, this point is assumed to represent the centre of the road. However, this method cannot ensure that the central region and the road centre are perfectly aligned. A more exact method would have been to conduct a calibration session before testing, for each participant, where they are asked to fixate on the road centre for a few moments. These fixations could then be used as a more accurate reference point for a central region anchor point. It is also challenging to use the faceLab eye-tracker to accurately link gaze points to static objects in the scene by only using only the PRC technique because the position of static objects relative to the location of the central area of interest varies between participants. Therefore, a calibration session before testing, for each participant, could be expanded to include reference points for other areas of interest in the cabin, for example, wing mirrors or dashboard.

Driving simulator

There are a number advantages and disadvantages when using driving simulators compared to real vehicles to examine driver performance. Simulators offer a controllable virtual environment with the ability to expose drivers to dangerous driving scenarios without putting them at risk (De Winter et al., 2012). Moreover, as there are few real-world examples of Level 2 and Level 3 automated driving systems, simulators are useful for mocking up these future systems. There is evidence to suggest that, for manual driving, simulator measures are predictive of on-road performance (Allen et al., 2007). However, it is unclear whether the same applies for how drivers would use automated driving systems on the road, as behaviour in this context may be more dependent on drivers' experience with the system, which is hard to emulate in a controlled testing environment.

The motion-based University of Leeds Driving Simulator provides a high degree of physical, perceptual, and behavioural fidelity. However, there were some issues encountered during the experimental testing. The first was that the simulator steering wheel does not have the ability to self-correct while in automated driving mode, which posed a problem when drivers attempted to resume manual control. For instance, if there were a steering wheel offset and drivers disengaged automation by depressing the brake pedal then the vehicle would adjust its trajectory to the steering wheel angle as soon as automation disengaged. Alternatively, if there were a steering wheel offset and drivers attempted disengage the automation by steering, then a proportion of drivers' subsequent steering action would have been to stabilise vehicle control. The second issue was that the simulator does not have an automatic braking system, which means that, in some cases, while drivers had the brake engaged in response to the lead vehicle, they were unable to steer. These two limitations resulted in some cases being excluded from the analysis, either because drivers were able to avoid a collision based on a large initial steering wheel angle at the point of take-over, or because drivers collided with the lead vehicle but not because of their own actions.

Performance measures

When analysing driver performance in automation, two approaches can be taken. First, one can observe behaviour and compare performance against some pre-defined estimates/measures. However, given that 'good' performance in automation is a relative unknown, at least regarding the traditional metrics, such as accelerations and steering measures, this approach may be redundant. This analysis approach was taken in Chapter 2 and Chapter 3, and its limitation was highlighted in both instances, which spurred the work presented in Chapter 6. That is, not simply how did drivers perform, i.e. what was their maximum lateral acceleration, but rather how did drivers perform relative to some meaningful expectation, i.e. could drivers match their response to the criticality of the event.

Second, once can use a well-known and accepted safety outcome, for example, collision outcome, as was used in Chapter 5. However, collisions are rare, and their frequency may equally be a reflection of system design, and experimental scenario under investigation. Perhaps, a more accurate approach might have been to assess a continuous safety outcome variable, such as minimum time to collision (minTTC) for drivers who do not crash (Jonasson and Rootzén, 2014) and DeltaV for those who do crash (Buzeman et al. 1998; Kusano and Gabler, 2010; Viano and Parentea, 2010). minTTC and DeltaV are well-established scales of outcome severity for near crashes and crashes, respectively. Such an approach would be useful to understand with greater accuracy what measures contribute to an unsafe outcome, but also what is an acceptable level of risk.

As argued in Chapter 6, although $t_{take-over}$ and the associated t_{action} provide a general indication of drivers' responsiveness, they do not necessarily provide a holistic view of whether drivers were prepared to resume manual control. Regarding crash outcome, our results seem to suggest drivers' ability to match their response to the event criticality was not as significant as I had proposed initially, which questions the weight placed on the recovery of physical vehicle control following the transition, by previous studies (e.g. Russell et al., 2016). Perhaps, as is implied in the concern within the aviation domain, that de-skilling of pilots' manual control as a result of excessive use of automation, is a longer-term adaptation (Wiener, 1988).

7.4 Contribution to the field and outlook

Investigating drivers' behaviour in, and interaction with, automated vehicle systems presents a challenge for human factors researchers. These can be confounded by some factors relating to technological advancement, policy implementation, and legal and ethical issues. The work presented in this thesis has contributed to an area suffering from a paucity of research, and while there has been a recent surge in this field, there is still a lack of consensus, on many of the most important human factors related issues. The work presented in this thesis does not provide a comprehensive investigation into all of these factors, and further work is required to build a consensus appreciating the dependencies of all related factors, though an overview of my proposition is given in Figure 7.1.

Figure 7.1 expands on the OoTL schematic presented in Chapter 3, to incorporate findings from this thesis into a larger framework, considering both Driver and Vehicle/Environment factors that are deemed to have an effect on driver performance in the transition. Here, the argument is maintained that Situation awareness and Physical control are the two key underlying factors to consider when investigating driver's capabilities and limitations in the transition. These can, however, be influenced by some Driver and Vehicle/Environment factors, which themselves may have interdependencies. The following section presents a brief exposition on these. Note that this model is not intended to represent or supplant a "joint" DVE (Driver-Vehicle-Environment) cognitive system, such as those presented in (Carsten, 2007) or (Cacciabue et al., 2013). Furthermore, the model does not account for all factors that will influence performance in the transition.

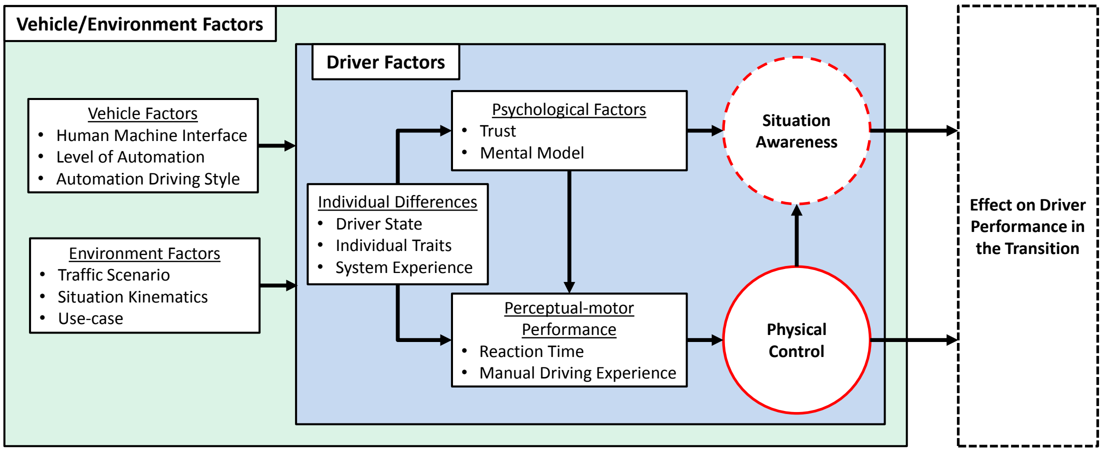

Figure 7.1: Studying the transition in highly automated driving.

7.4.1 Driver Factors

This thesis has mainly considered the Driver factors influencing driver performance in the transition.

Physical control

First and foremost, automation decouples drivers from the Physical control loop of the driving task. The successful re-coupling of drivers to the physical control loop will depend on their Perceptual motor performance, which describes their capacity to match the physical control response to the requirements of the situation, as investigated in Chapter 6. This thesis has shown that L2 and L3 automated driving systems will, under certain circumstances, negatively influence how drivers can perceive and respond to unexpected events in automation. However, here and elsewhere these findings are often interpreted with the assumption that Driving skill and their Manual driving experience will remain intact. Future work should consider how these may be vulnerable to decay through a lack of experience just as pilots' manual flying skills have been shown to deteriorate following the prolonged use of autopilot systems (Wiener, 1988). Indeed, evidence is emerging in support of driver training, for specific scenarios in automation (Hergeth et al., 2016), but quite how such programs can be designed to be most effective requires investigation.

An additional factor relating to drivers' physical responses is their ability to respond in a timely and safe manner (Reaction Time). While in this thesis, the usefulness of the take-over time measure (and Reaction time measures in general) has been questioned, it is amongst only a few providing insight into drivers' behaviour in the transition, and, therefore, deserves regular attention. In parallel, however, future work should build on work presented in this thesis, to develop new analyses for establishing 'good' performance in the transition. Whether or not drivers are engaged in physical vehicle control will have some influence over how engaged they are in the driving task (Carsten et al., 2012), which will also have an impact on drivers situation awareness.

Situation Awareness

The second major Driver factor, as proposed in Chapter 3, is drivers' Situation awareness, which is defined as "*the perception of the elements in the environment within a volume of time and space, the comprehension of their meaning, and the projection of their status in the near future*" (Endsley, 1995). Within the context of transitions in highly automated driving, there are a number of Psychological factors that may influence driver SA, such as Driver state, for example, attentional control, stress, fatigue, and workload, but also drivers' Mental model of the system and their Trust in it.

While it was not a direct focus of this thesis, drivers' Mental model of the systems they are operating is clearly an important factor to consider. With no clear international regulations governing the type or consistency of the systems used to enable automated driving technologies, a vast array of systems and products available to consumers will soon emerge, each with slight variations in their capabilities and operation. Therefore, on the one hand, it is important that engineers and designers understand what their users understand and are capable of, but on the contrary, it is essential that drivers are educated about the capabilities and limitations of the system they are using (Hollnagel and Woods, 2005).

Linked to Mental models, drivers' Situation Awareness will also be mediated by their Trust in the automated driving system, which has received some attention in recent years (cf. Beukel and Voort, 2014; Gold, et al., 2015), and where over-trust has been observed to have a negative effect in the context of system failures in automation (Shen and Neyens, 2014). It is important that studies acknowledge and calibrate the level of drivers' trust in the automated driving systems with which they will be interacting.

Individual differences Finally, it is important to acknowledge that Individual differences may have an effect on both Situation awareness and Physical control. Individual differences can relate to drivers' Individual traits, for example, personality, demographics, and trust propensity. Also, drivers' System Experience will have a mediating effect on their Mental Model, but also regarding their physical control response when resuming control, i.e. understanding what steering torque will help contribute to corrections of heading errors. Certainly, there is evidence that behavioural adaptation to support systems changes over time (Markkula et al., 2012), and recently evidence has suggested the same for L2 and L3 automation (cf. Gold and Bengler, 2014; Beukel and Voort, 2014; Carsten et al., 2012; Petermann-Stock et al., 2013). The studies presented in this thesis capture behaviour and performance of drivers who have little or no short-term or long-term exposure to these automated driving systems, yet, a clear learning effect has been found in almost all scenarios considered. Not only is it important to understand longer-term behavioural adaptations, but also how they develop in more naturalistic settings. While a driving simulator provides a controlled environment ideal for studying safety critical situations, it does not capture the complexities of real-world driving, which the driver would be subject to, in naturalistic settings.

7.4.2 Vehicle/Environment Factors

The Vehicle/Environment Factors relate to the road and traffic scenario factors and the vehicle design factors that are hypothesised to have an effect on performance in the transition, in terms of drivers' ability to perceive, comprehend, and predict (situation awareness) the unfolding event, but also their ability to react to it (perceptual-motor performance).

Vehicle factors

Vehicle factors relate to the Human-machine interface, the Level of automation being transitioned to or from, and the system's Automated driving style.

The Human-Machine Interface (HMI) comprises of the interface design, which determines the quality of system feedback it provides to drivers, as well as the interaction design, which specifies interaction principles and how control is arbitrated, for instance the dynamic distribution of control proposed in the H-mode project (Flemisch, 2003; Bengler and Flemisch, 2011). A number of HMI concepts to improve driver performance in the transition have been evaluated in a range of settings (e.g. Petermeijer et al., 2015, and see Manca et al., 2015 for a review), but this thesis has shown that the information drivers have available to them during the transition is an important aspect to consider. Therefore, further work will need to find more driver-centric HMI solutions.

It follows that systems will vary regarding the degree to which they are able to assume control of the driving task (Levels of automation). It is well established that the extent to which a task is automated influences how users interact with that task, therefore, it is important to consider how this behaviour influences performance in the transition.

Automated driving style refers to the system-based principles of vehicle control, for example, the trajectory and acceleration profile adopted by the automated driving system. Future work should consider whether drivers prefer HAD control characteristics that are human-like or not, as this may influence system acceptance and use.

Environment factors

relate to the urgency of the unfolding situations, which may be affected by the Road Type, for example, highway, rural, or sub(urban) roads, and Traffic scenario, for instance, traffic density, or position relative to surrounding vehicles (especially visual looming). Recent simulator studies have not found consensus on the effect of different traffic situations on performance in the transition (Radlmayr et al., 2014; Naujoks et al., 2014). However, many of these will require constant reassessment as new L2 and L3 systems with different capabilities and characteristics are released to the market. In comparison to studies of manual driving, investigations related to the tactical- and strategic- levels of driver performance in the transition in automated driving are somewhat limited. Besides, and as outlined above, the experimental use-cases and HMI used in these studies are as varied as their findings. Consequently, a clearer picture of drivers' capabilities and limitations in their interaction with vehicle automation can be achieved by more similar methodologies. In addition to the above, it is important to consider the kinematics of the situation under investigation Situation kinematics, as this may not only help compare results from studies with slightly different take-over situations, but it also provides a means to analyse performance based on drivers' response to some threat in the road environment. Finally, adverse Weather conditions may also have some impact on drivers' performance in the transition. For example, rain can obscure the vision of onboard cameras and reduce the range and accuracy of laser-based Lidar sensors, which would potentially trigger a high workload transition scenario.

7.5 Final conclusion

The main theme throughout this work is that automation affects the cognitive (visual attention) and physical (perceptual-motor) aspects of driver vehicle control in the transition. Under some conditions, automation had a stronger effect on the cognitive aspects, while in others the physical aspect dominated. As such, they should be considered in concert to gain a holistic understanding of the effect of automation on driver performance in the transition.

7.6 References

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