Allocation of Visual Attention during Transition from Vehicle Automation

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Intellectual Property and Publications

The candidate confirms that the work submitted is his/her own, except where work which has formed part of jointly-authored publications has been included.

A total of six publications have been produced from research that was undertaken as part of this thesis. Each publication is listed below with a full reference details of its location within the thesis. 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.

The work in **Chapter 2** of the thesis has appeared in a publication as follows: Goncalves, R. C., Louw, T. L., Quaresma, M., Madigan, R., & Merat, N. (2020). The effect of motor control requirements on drivers' eye-gaze pattern during automated driving. Accident Analysis & Prevention, 148, 105788.

The candidate contributed with the majority of the data interpretation, analysis, and wrote the whole article. TL and RM were responsible for the data collection and study design. NM and TL were responsible for the overall supervision of the data analysis and interpretation process, with contributions from MQ and RM. All authors actively contributed for the editing and revision of the final version of the manuscript.

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This publication was presented in the form of a poster presentation on the TRB conference and was available on the event proceedings. The candidate was responsible for a substantial part of the study design and data collection, as well as for the full data analysis and full writing of the manuscript. VR and GT were also responsible for a significant part of the data collection and study design. PP was the project leader and industrial partner for the research. TL and NM were the main supervisors of the whole project. All authors actively contributed to the revision of the final version of the manuscript.

The work in **Chapter 5** of the thesis has appeared in a publication as follows: Goncalves, R. C., Louw, T. L., Madigan, R., Quaresma, M., Romano, R., & Merat, N. (2022). The effect of information from dash-based human-machine interfaces on drivers' gaze patterns and lane-change manoeuvres after conditionally automated driving. Accident Analysis & Prevention, 174, 106726.

The candidate was responsible for a significant part of the study design, the complete process of data collection, analysis and interpretation of the results, as well as the writing of the manuscript. RM, RR, and MQ were responsible for contributions on the data interpretation and provided support on the writing of the manuscript. TL and NM were the main supervisors of the whole project.

The work in **Chapter 6** of the thesis has appeared in a publication as follows: Gonçalves, R., Louw, T., Markkula, G., & Merat, N. (2019). Applicability of risky decision-making theory to understand drivers' behaviour during transitions of control in vehicle automation. Ergodesign & HCI; HCI, Vol. 7, 36-50. Doi:10.22570/ergodesignhci.v7iEspecial.1304.

The paper has a fully theoretical nature, and no empirical data was presented. It was presented in the Ergodesign/USIHC 2019, in Rio de

Janeiro, and then published in an extended version as an invited journal paper for the Ergodesign & HCI journal. The candidate was responsible for the conception of the manuscript, main theoretical discussion and writing. All the other three authors actively participated in the discussion and interpretation of the literature review, and revision of the manuscript.

The work in **Chapter 7** of the thesis is a journal paper ready for submission, entitled: Gonçalves, R., Louw, T., Lin, Y., Markkula, G. Merat, N. (ready for submission). Evidence-accumulation model to predict forward collision reactions in a conditionally automated vehicle using drivers' gaze. The candidate was responsible for the data analysis, interpretation and writing of the manuscript. NM and TL were the main supervisors of the project. TL was responsible for the data collection for the experimental data presented in the manuscript, and GM and YL were responsible for technical support and conceptualization of the mathematical model presented.

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Abstract

This research aimed to investigate how the way drivers allocate their visual attention across their environment affects their process of decision-making about a resumption of control from vehicle automation. It also aimed to investigate how different factors such as the involvement of the driver with the decision-action loop; situation kinematics and presence of supportive information affect this relationship between gaze and decision. This research's motivation came from an inherent issue on the topic of the transition of control: The high amount of spread visual information required from the driver to perform a manual intervention safely. This issue forces the driver to prioritise certain information over others, which may lead to different outcomes for their take-over reaction. There is a lack of empirical evidence showing the link between the way drivers sample information and their abilities to perform an appropriate transition of control. By understanding how drivers should look to enhance their decision-making process, it may be possible to develop guidelines and recommendations for designing suitable HMI, and strengthen driver performance during a take-over from automation.

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List of Abbreviations

Several 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.

AOI Areas of Interest.

DMT Decision-making time

DDM Drift-diffusion Model

EAM Evidence Accumulation Model

HMI Human Machine Interface.

LBA Linear Ballistic Accumulator Model

ML Machine Learning

NHTSA National Highway Traffic Safety Administration.

OoTL Out of the loop.

PRC Percent Road Centre.

SA Situation Awareness.

SAR Situation Awareness Recovery.

SAE Society of Automotive Engineers.

SD Standard Deviation.

TOR Take-Over Request.

TB Time Budget.

TTC Time To Collision.

TW Time Window

“There is a belief among many automation engineers that one can eliminate human error by eliminating the human operator. To the extent a system is made less vulnerable to operator error, it is made more vulnerable to designer error (Parasuraman & Riley, 1997). And given that the designer is also human, this simply displaces the locus of human error. In the end, automation is really human after all.”

Parasuraman & Sheridan (2005)

1. Introduction

1.1 General Introduction

In recent years, we have been witnessing a constant growth in the development of vehicle automation technologies, with predictions for it to represent a good portion of the automotive market in the near future. Global market predictions (Precedence Research, 2022) estimated that the autonomous vehicle market value was around USD 94.43 billion in 2021 and is projected to grow up to USD 1808.44 billion by the year 2030. This corresponds to an estimated 38.8% compound annual growth rate, which is remarkably higher than many of the most prominent markets, like the mobile app industry (13.4%, Grandviewer Research, 2022a), and streaming services (21.3%, Grandviewer Research, 2022.b). This rapid growth is attributed to government support from many nations of the world, advances in legal and regulatory frameworks for its implementation, and the promise to revolutionise the roadway transportation structure (Precedence Research, 2022). The presence of vehicles already capable of assuming both lateral and longitudinal control of the driving task (e.g. Tesla Model S; Tesla, 2022) in the open market is a good indication that such technology is here to stay.

Amongst the promised benefits attributed to vehicle automation is the improvement in Traffic flow, costs and fuel consumption (Fagnant & Kockelman, 2015), an extension of driving mobility for impaired or older drivers (Young & Bunce, 2011), and, most notably, the reduction of human error as a cause of accidents, which is a significant issue in road safety (Horberry et al., 2006). On the other hand, despite all the expected benefits of vehicle automation, technology only explores a finite set of pre-defined scenarios, where the automation can operate with maximum reliability (limited operational design domain, SAE, 2021) and might require the human driver to resume control of the driving task, whenever a system limitation is reached (NHTSA, 2016). This issue highlights a conceptual controversy inherent to the human interaction with automation (Parasuraman & Sheridan, 2005); that humans have their cognitive resources deviated from the task, yet, they are still required to intervene, whenever solicited, or whenever the automation faces a system limitation of malfunction. This reminds us of a profound irony: the more reliable (yet not perfect) the automation, the less prepared the human being is to respond when they are most needed (Bainbridge, 1983).

According to Merat et al. (2019), the removal of drivers from the physical and cognitive (specifically for L3 automation) control loops of the driving task in an automated environment significantly jeopardizes their levels of situation awareness (Endsley, 1995) and visuo-motor coordination (Wilkie & Wann., 2010), which are both paramount for the human's ability to drive safely. Therefore, to safely respond to a system limitation and successfully recover control of a vehicle, drivers need to engage in a recovery process and re-acquire sufficient levels of both resources (situation awareness and visuo-motor coordination) in a timely manner, given the situation at hand (Mole et al., 2019; Damböck et al., 2013). Unfortunately, the re-insertion of the driver in the loop has proven to be a challenging task (Endsley & Kiris, 1995) due to the high amount of information that needs to be sampled in a limited time span, which may end up overloading drivers' information process resources (for more details about this process, see Goodrich & Boer, 2003). Therefore, it is the duty of the Human Factors community studying vehicle automation to understand how drivers allocate their limited attentional resources to resume control of the driving task. By understanding the cognitive processes underlying a transition of control, it may be possible to provide tools to support human drivers in such tasks and thereby improve vehicle safety.

Driving simulator studies in this context (Louw et al., 2016; Louw et al., 2018; Zeeb et al., 2015), as well as studies related to forward collision avoidance (Xue et al., 2018; Svaard et al., 2020; Markkula et al., 2016) have suggested that the drivers' reaction time to critical situations and the safety outcome of their reactions can be causally-correlated with certain gaze patterns. Furthermore, drivers' takeover performance is also linked to attention directed to certain aspects of the road environment, such as an early attention to the hazard in front, in case of a rear-end collision. This assumption is supported by experimental and conceptual research on theories of risky decision-making (Edwards, 1954; Orquin & Loose, 2013), and bounded rationality (Boer, 1999; Simon, 1972; Goodrich & Boer, 2003), which suggest that decisions (in the case of this work, the reaction to a takeover request) are constantly biased by the information gathered by the decision-maker (which is primarily via visual sampling). Therefore, if the decision-maker (driver) is under time pressure and is not able to process all the information at their disposal (as suggested by Goodrich & Boer, 2003 and Gold et al., 2013), one can assume that their reaction outcome will be influenced by the way they visually sampled the environment.

The studies mentioned above suggested that there is a correlation between the way drivers sample their environment during a transition of control and the probability of a safety outcome of the situation. With that in mind, one can assume that we can use drivers' gaze to understand what can be considered a safe resumption of control. However, it is well agreed that gaze scanning patterns are sensitive to environmental manipulations (Carrasco, 2011; Borji & Itti, 2013). For instance, the presence of vehicles in the surrounding environment, or on-screen driver assistance-based information is known to affect the way drivers scan their environment (see Ali et al., 2021). To better understand how drivers allocate their visual attention to resume control from an automated vehicle, it is necessary to systematically manipulate the attentional saliences of the scenario, and understand how each aspect related to the transition process affects drivers' gaze patterns, and then, observe the correlation between drivers' gaze and a safe resumption of control.

This research uses, as its main theoretical background, the concepts of situation awareness (Endsley, 1995) and situation awareness recovery (Gartenberg, 2014), together with principles of risky decision making theory (Edwards, 1954) and bounded rationality (Simon 1972) to understand how drivers allocate their visual attention across the environment to recover control from vehicle automation. The following sections of this chapter will provide a critical literature review of the main topics related to this research, leading to a summary of the main research gaps, followed by the objectives of this research programme and the research questions that were used to address these gaps.

1.2 The role of visual information in the driving task

Since the early human factors research on driving behaviour, it is well-accepted that the majority of the safety-related information associated with the driving task relies on the visual modality (Sivak, 1996; Cloe, 1972; Sanders et al., 1967). Visual information processing is regularly associated with some of the core activities of driving, such as the visuomotor coordination of locomotor control (Wilkie et al., 2008), hazard perception (Horswill & McKenna, 2004; Crundall et al., 1999), and interaction with non-driving-related activities or secondary systems (Metz & Schoemig, 2011). However, according to Trick & Enns (2009), each of these activities make use of different elements of the visual attention selection structure in the human brain. To better understand the relationship between visual attention and driving, this section will present the core principles in the visual attention literature, and later describe how each of those principles are used in the most common activities that constitute the driving task.

1.2.1 General concept of attention as stimulus selection and information processing

The concept of attention (whether visual or not) can be defined as the operant process of segregation and identification of a given discriminated stimulus in an environment containing other non-discriminated stimuli (Skinner, 1953). In other words, attention is inherently a selective process, caused by the limited capacity of the brain to simultaneously process all the information available at our disposal (Carrasco, 2011). In this process, individuals differentiate relevant (signal) and irrelevant (noise) elements, based on semantic associations of the targeted stimulus' discriminative features (see Figure 1.1 for a schematic representation of the process). As an example, in early signal detection studies, Skinner (1953) was able to train pigeons to recognise and respond to a flashing red light in an apparatus, suggesting that their trained response was a discriminative response to a given phenomenon (light on/off).

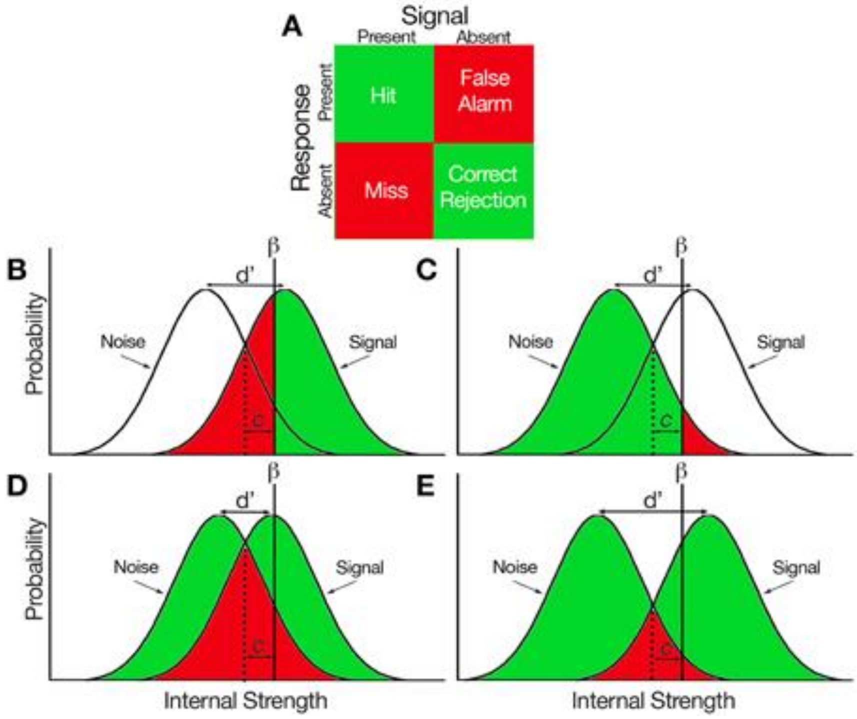

Figure 1.1 Schematic representation of the selective process of attention (Makowsky, 2018). Panel A represents the four possible outcomes of a signal detection task. Panels B-E show a graphical representation of the outcomes mentioned in A (Hit, False Alarm, Miss and Correct Rejection, respectively).

In his emblematic cueing experiment (Figure 1.2) Posner (1980) was able to show that, when it comes the stimulus, the brain mechanisms responsible for the segregation and selection of stimuli (attention) is causality-correlated with the spatial position of the individual's gaze focus. In other words, Posner's work (1980) showed that individuals tend to fixate their eyes towards and on the elements in the environment they are attending to. Based on these findings, research in modern applied psychology relies on the location of gaze as a proxy for the location of attention and information processing, to understand the structure and process of attention selection.

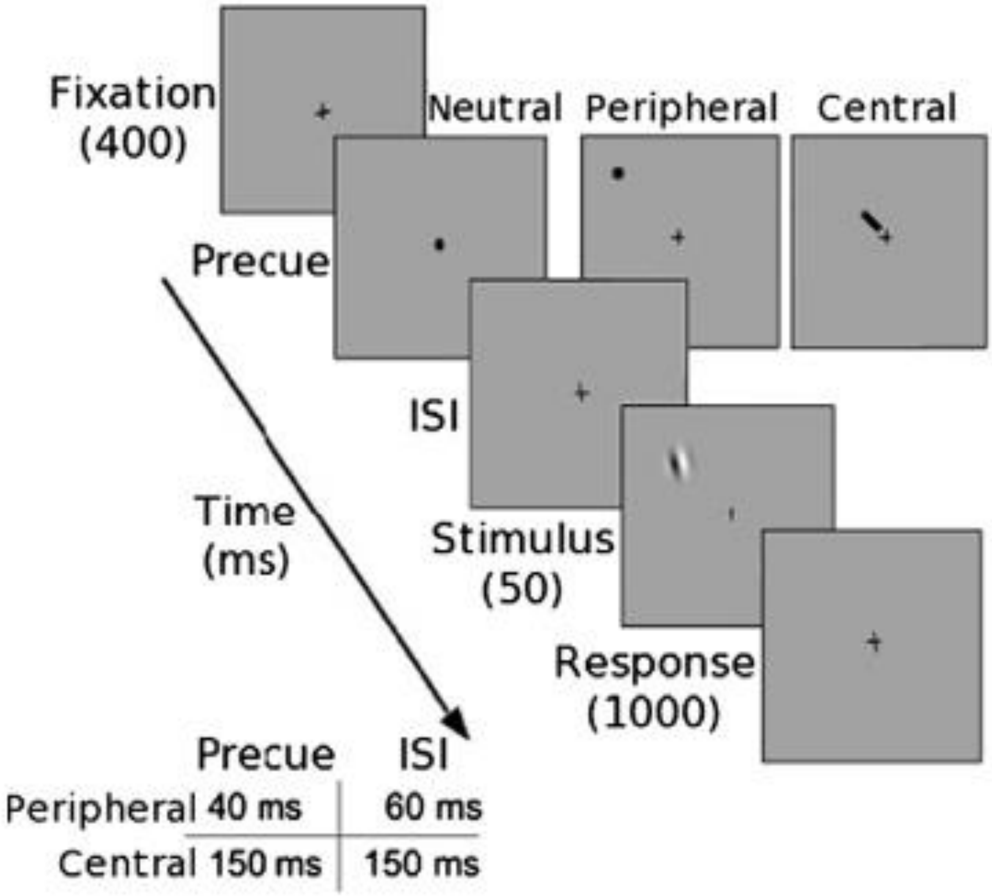

Figure 1.2 Representation of Posner's (1980) cueing experiment

On the other hand, this proxy assumption should be used with care. Posner's (1980) research has also shown that visual attention can be drawn from the periphery of an individual's field of view. In this sense, it is safe to assume that mechanisms for information source and signal discrimination are present even when the individual is not actively fixating to an object. Other thing that should be considered is that prolonged gaze towards one fixed area is also one indication of mind wandering, or confusion (see Walker & Trick, 2018). Walker & Trick (2018) have shown in driving simulator studies that drivers fixating staticly on the road ahead were not necessarily paying attention to the road, but rather had no particular focus on any driving-related or visual information-related activity. In that sense, one should be mindful that not all information to be processed by the human brain is necessarily visual, and therefore using gaze as a proxy of information processing may lead to misinterpretation of the human behaviour. Despite this fact, given the nature of the driving task (Sivak, 1996), and how resource demanding it may be, this may be one a reliable way to assess drivers' behaviour, since it is unlikely for a driver to be executing an active manoeuvre in a vehicle, without processing information about it.

1.2.2 Structures of attention selection

According to Carrasco (2011), there are two main sets of structures that orient the process of attention selection: 2) feature-based (bottom-up/top-down) and 2) spatial (covert/overt attention), which will be discussed further in this subsection:

Nakayama & Martini (2011), and Carrasco (2011) have shown that visual information acquisition is a serial (sequenced) selective process, due to the brain's inability to process large amounts of information at once (Lennie, 2003). That said, feature-based structures of attention are cognitive mechanisms that modulate the priority given by an individual's attention to certain information sources, dictating the order in which they will be visually sampled. The first structure of sequential selection is the **top-down structure**, which guides the sequence of eye movements, based on the individual's expectancy to find a given set of information at a certain location. This structure makes use of resources such as long/short-term memory and experience of the individual, and their mental model of the task in hand, to semantically discriminate the signals in the environment, and guide the eye movements in a planned, goal-directed, approach (Borji & Itti, 2013). The opposing, but sometimes complementary, **bottom up structure**, relies on the saliency of signals (also relevant to the context, when compared to the other elements in the field) attracting the individual's gaze, without a predefined pattern (Borji & Itti, 2013). It must be noted that these structures are not mutually exclusive, and they can coexist in a visual search task, where individuals generally follow a given top-down path, which may be regularly disrupted by bottom-up saliences in the environment.

As previously mentioned, visual attention allocation is generally associated with the movement of the eyes towards the stimulus that is being identified and discriminated in the environment (Posner, 1980). Here, spatial attention selection structures are the ones that control the movement of the eyes, and allocate the attention resources towards a signal (Carrasco, 2011). **Overt attention** is the cognitive mechanism that modulates the actual focus of the individual's attention towards the location their eyes are fixating (Carrasco, 2011). On the other hand, **covert attention** is the cognitive mechanism that modulates the minor degrees of attention given to the periphery of the individual’s field of view. According to Carrasco (2011), signals can be discriminated in a general area, by the covert attention structure, which consequently guides the eyes towards the spatial location of the signal, and therefore starts to be mediated by the overt attention structure.

By closely observing both sets of attention structures, one can assume that they are deeply entwined, in a way that covert structures may lead to bottom-up manipulations of attention, in the same way that a top-down structure might guide one’s overt attention to specific elements which were not necessarily captured by the covert attention beforehand. In fact, many studies (Hayhoe & Ballard, 2009; Borji & Itti 2013) have concluded that eye movements and attention allocation patterns are heavily dictated by the scenario in hand. One example for that assumption is the fact that we expect drivers to look towards their side mirrors, as they are about to change lanes. The interactions between attention selection structures may change, given the situation the individuals are facing. Also, even different individuals might be affected differently by the same aspects of the environment, performing similar (but not identical) eye movement patterns, due to contextual manipulations. With that in mind, it is necessary to understand which contextual elements of the driving task (both manual and automated) dictate the way drivers move their eyes, in order to control their vehicles.

1.2.3 Information processing models for driving

In the early 1980s, Rasmussen (1983, 1986) developed a conceptual model of human information processing during the interaction with complex systems. Later in the decade, Michon (1985) revisited Rasmussen’s model, adapting it for the specificities of the driving task, and the information processed for each of the minor activities therein. Both Rasmussen’s (1983, 1986) and Michon’s (1985) models divide the information processing routines of human behaviour into 3 levels: 1) skill-based, 2) rule-based, and 3) knowledge-based (see details inFigure 1.3).

In the context of driving, the **skill-based** (control) level is composed of micro and constant activities (taking a matter of milliseconds), where drivers process sensorimotor information from the environment to adjust the vehicle’s heading and/or speed, to match with their higher-level strategic goals. The **rule-based** (manoeuvring level) is composed of conscient, strategic decisions, made over the course of seconds, based on well-learnt procedures, such as changing lanes, and negotiating a curve. The

knowledge-based (strategic) level is composed of higher-level decision-making procedures, which are generally planned beforehand, such as route selection to get to a place, generally using drivers' previous knowledge of the situation, such as the distance to the destination, traffic jam locations, and use of alternative routes.

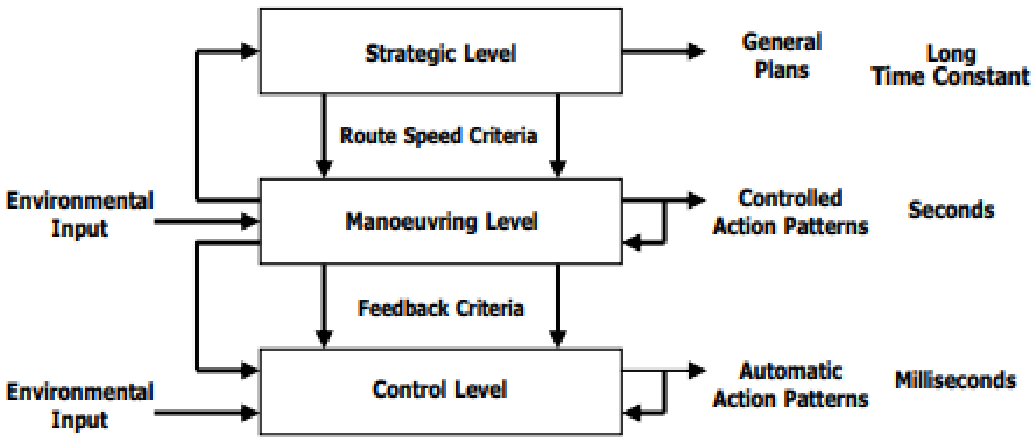

Figure 1.3 Michon's (1985) levels of information processing for the driving task

Based on this model, many authors (e.g. Hollangel & Woods, 2006; Behere & Torngren, 2015; SAE, 2016) describe the driving task as a constant "observation-orientation-decision-action" (OODA) loop (see Boyd, 1976), where information from the three hierarchical levels is constantly processed, in an iterative cycle, yielding moment-to-moment decisions that feed information for the next repetition of the loop. As described by the Society of Automotive Engineers (SAE, 2016) and Merat et al. (2019), the control loop of the driving task can be divided into minor closed-end loops (see Figure 1.4), where information from a higher hierarchy is processed first, providing input for lower hierarchies until a high-level goal is translated into a sequence of motoric inputs for the vehicle's control. In other words, major goals, such as arriving on time to a given location (strategic level of information) will lead drivers to conduct overtaking manoeuvres (manoeuvring level), which can be translated into the manual force applied to the steering wheel and pedals (control level), to move the vehicle towards its intended path and reach the final, desired, destination.

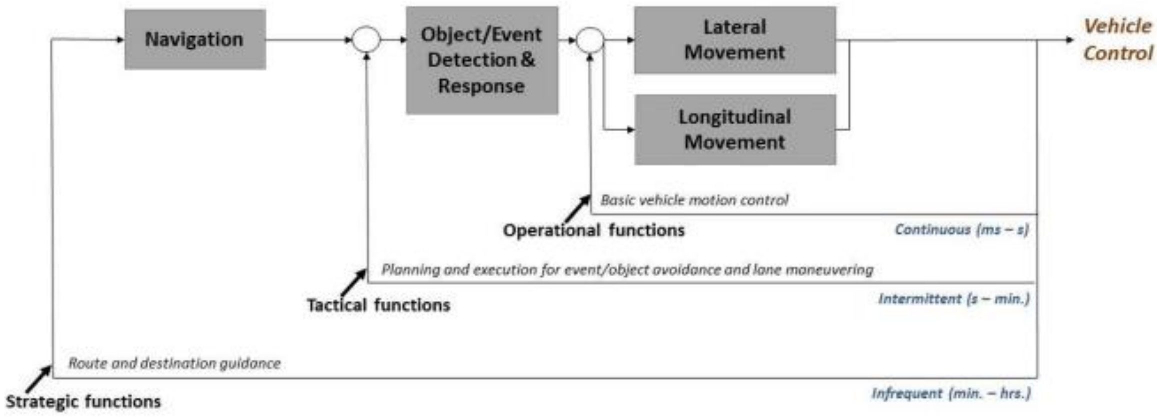

Figure 1.4 Merat et al.'s (2019) diagram of the information processing loop of a driving task

When it comes to how information is visually acquired for processing in a driving task, Tick & Enns (2009) defines a two-dimensional framework, where all scanning routines, commonly associated with the driving task, can be divided into four modes of attention selection (see Figure 1.5): 1) reflex, 2) habit, 3) exploration, and 4) deliberation. The two dimensions of the framework are similar to Carrasco's division between covert/overt attention selection structures and top-down/bottom-up structures, however with different terminology (endogenous/exogenous, automatic/controlled).

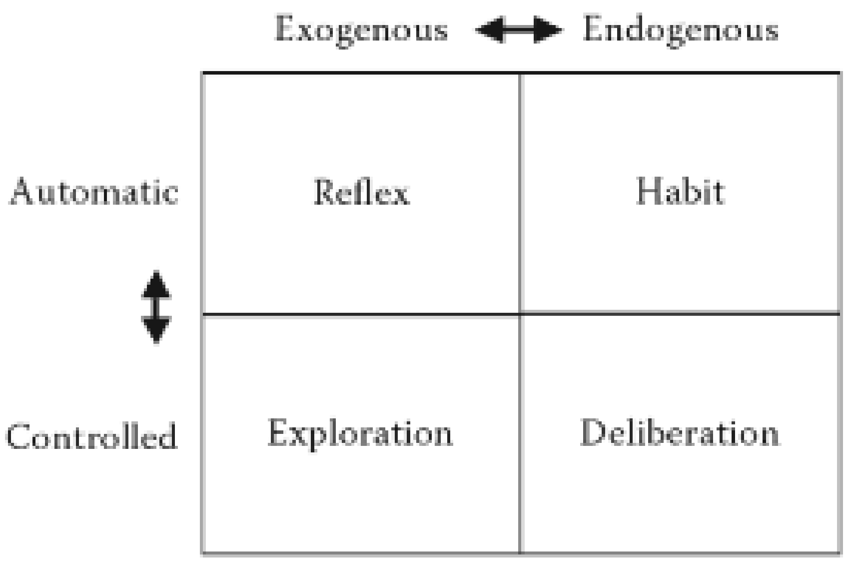

Figure 1.5 Trick & Enns' (2009) diagram of attention selection modes of the driving task

Reflexive (automatic-exogenous) selection of attention is an unconscious, obligatory response to a salient stimulus or event. Generally, this process occurs when a given stimulus is so evident in the drivers' field of view that it naturally attracts their overt attention (bottom-up manipulation of attention). Examples include drivers' direction of attention during a near-crash event, where the looming (optical expansion of the size of an object through motion) of an approaching obstacle attracts the driver's attention. **Habitual** (automatic-endogenous) selection of attention is an unconscious visual scan routine, done by habit, as part of a conditioned behaviour (top-down structure). According to Trick & Enns (2009), this constitutes the majority of our gaze behaviour while driving, as it mediates the most common strategies used to perform tactical decisions in a driving task (e.g. looking to the side mirrors before changing lanes). It must be noted that all routines in this mode of attention selection are learned, as the driver gets used to habitual situations, and knows by experience where to find the most relevant information source, at any given time, as an automatized behaviour (Engström, 2011).

The **Exploratory** (controlled-exogenous) selection mode of attention governs where the driver focuses their attention whenever there is no specific goal for the task (hence, no discriminative features of a stimulus). This mode is mainly mediated by a bottom-up structure, where the drivers' covert attention is sensitive to many potential attentional saliencies that are distinguished from the habitual road scenario (e.g. aeroplanes in the sky, speeding vehicles in the surroundings, and advertising boards, etc...). It must be noted that such exploratory gaze can lead to driver distraction, since the ocular perception channel is not able to focus on multiple locations at once, and drivers exploring the environment are more likely to focus their attention on non-driving related stimuli, which increases their distraction from the main driving task. At last, **Deliberate** (controlled-endogenous), attention selection mode is defined as driver visual scanning behaviour in non-routine situations (e.g. taking over control of vehicle automation, negotiating an overtaking manoeuvre, responding to a critical near-crash scenario, etc...). This mode of attention can be part of a top-down structure of attention, where drivers consciously look for specific information during a specific situation, while reacting to specific contextual elements of the scenario. Such Deliberate gaze patterns are generally associated with individual differences in crash risk (Trick & Enns, 2009), with experimental studies showing that drivers who were able to avoid a crash, presented a significantly different gaze patterns, when compared with those who crashed (see Crundall et al., 1999; Engström, 2011 ; Louw et al., 2016).

Based on these links between gaze patterns and crash propensity, it can be argued that drivers' gaze behaviour before and during a transition of control and can be modelled to predict their ultimate safety, upon resuming control from automation. As gaze behaviour is generally correlated with probability of crash outcomes in a driving scenario (Engström, 2011), it is possible to identify a "safe gaze pattern" (as suggested by Horswill & Mckenna, 2004). In light of this theory, it is important to understand what kind of visual information should be acquired, and when, to safely control the driving task.

1.2.4 Visuo-motor coordination

Research shows that visual information plays an essential role in human locomotion, as it provides us with the perception of movement needed to orient our trajectory and move in space (Wilkie & Wan, 2010). This perception of motion is provided by the "optic flow" (see Gibson, 1958) of moving elements, in a fixed plane of reference, projected onto our retina, which gives the brain the impression that the scenario is moving (or rather, the viewer is moving, therefore, changing the relative position of the elements in sight), as can be seen in Figure 1.6.

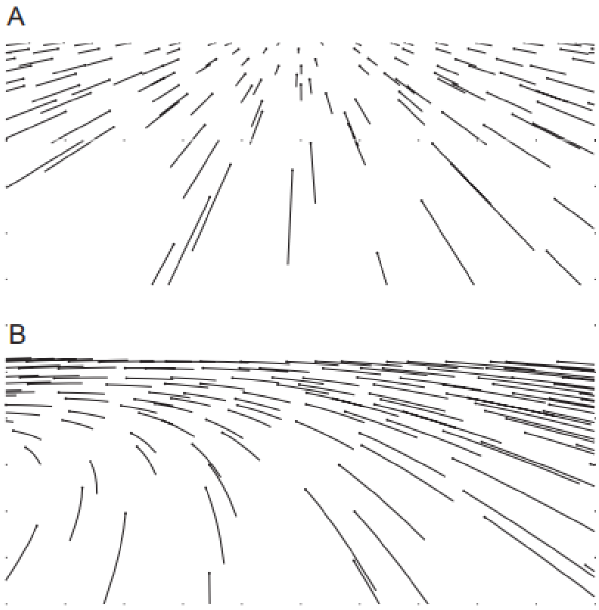

Figure 1.6 Wilkie & Wann's (2010), representation of optic flow

By using this perception of motion, drivers are capable of assimilating the steering wheel and pedal inputs with their consequential impact on the vehicle's motion (Land & Lee, 1994), such that steering movements and eye gaze are tightly correlated (a phenomenon called visuomotor coordination). Visuomotor coordination is not only related to optic flow, but also help us acquire the anticipatory information required for our next manoeuvre. Land (1998) proposed a two-point framework of gaze that can be divided into two main categories of gaze: guiding, and look-ahead, fixations**. Guiding fixations** are responsible for the moment-to-moment adjustments of the vehicle's heading and are generally focused in the close field of view, where drivers can notice small changes in the optic flow of the movement. On the other hand, **look-ahead fixations** are focused on the far field of view, aiming to collect pre-emptive information, to aid the driver with decisions on a tactical level of control.

1.2.5 Hazard Perception

In addition to visuo-motor coordination, which modulates the information processing for operational control of the vehicle's locomotion and direction, hazard perception is used to support drivers' tactical and strategic safety-related behaviour, involving a scanning of the environment, in order to avoid potential risks in the near future. According to Horswill & McKenna (2004, p2), *"Hazard perception has been described as the ability of drivers to anticipate potentially dangerous road situations. It has been recognized as being an aspect of driver skill that has critical implications for road safety and accident involvement"*. Therefore, when linked to Trick & Enns' (2009) taxonomy of attention selection modes, hazard perception routines are composed of habitual and deliberated gaze patterns, which involving seeking for discriminated stimuli that are known to cause potential crash scenarios.

These deliberate or habitual behaviours are known to be influenced by driving experience, and styles, influencing drivers' ability to detect threats, in simulated scenarios (Crundall & Underwood, 1998; Underwood et al., 2014). Indeed, these studies showed that some vehicle crashes were directly related to poor scanning patterns, and poor hazard perception skills (see Chovan, 1994). This provides further evidence that certain scanning gaze routines (such as mirror checks during lane changes, or wide saccadic eye movements to the sides of the road during free drive) can be associated with a safer driving style.

1.3 Vehicle automation and driver behaviour

Studies in the previous subchapter illustrated that drivers' gaze is an important part of understanding how the vehicle is controlled during manual driving. However, according to Parasuraman et al. (2000), the introduction of automation in a task completely alters its nature, in a way that it cannot be faced under the same perspective. This subchapter introduces the basic concept of human-automation interaction (HAI), and how control in an automated driving task differs from a manual driving task, and the relationship between this control and drivers' visual attention, and how that affects their safe control of the vehicle.

1.3.1 Levels of automation and driver roles

According to the National Highway Traffic Safety Administration (NHTSA, 2016), automated vehicles can be defined as motor vehicles capable of partially, or totally, controlling the lateral and longitudinal control of the driving task, without the active need for human interaction - within a particular operational design domain (ODD). In such circumstances, humans slowly lose their role as the active controller of the driving task, and in certain cases, such as SAE (2021) level 2 automation, assume a supervisory role (as defined by Dekker, 2005 and Parasuraman & Sheridan, 2005). There have been various attempts to create a taxonomy of these levels of automation. For instance, Parasuraman et al. (2000) proposed a ten-level scale for automated systems, that describes the degree of intervention in the human's task, and how much interaction is needed from the human for the goal to be achieved (see Figure 1.7).

HIGH 10. The computer decides everything, acts autonomously, ignoring the human.

9. informs the human only if it, the computer, decides to

8. informs the human only if asked, or

7. executes automatically, then necessarily informs the human, and

6. allows the human a restricted time to veto before automatic execution, or

5. executes that suggestion if the human approves, or

4. suggests one alternative

3. narrows the selection down to a few, or

2. The computer offers a complete set of decision/action alternatives, or

LOW 1. The computer offers no assistance: human must take all decisions and actions.

Figure 1.7 Parasuraman et al.'s (2000) levels of automation

Based on this structure, SAE (2021), developed their own levels of automation, tailored specifically for the context of vehicle automation, taking into account factors such as the role of the driver (longitudinal and lateral control, vigilance, etc...), and the operational design domain of the vehicle (see Figure 1.8).

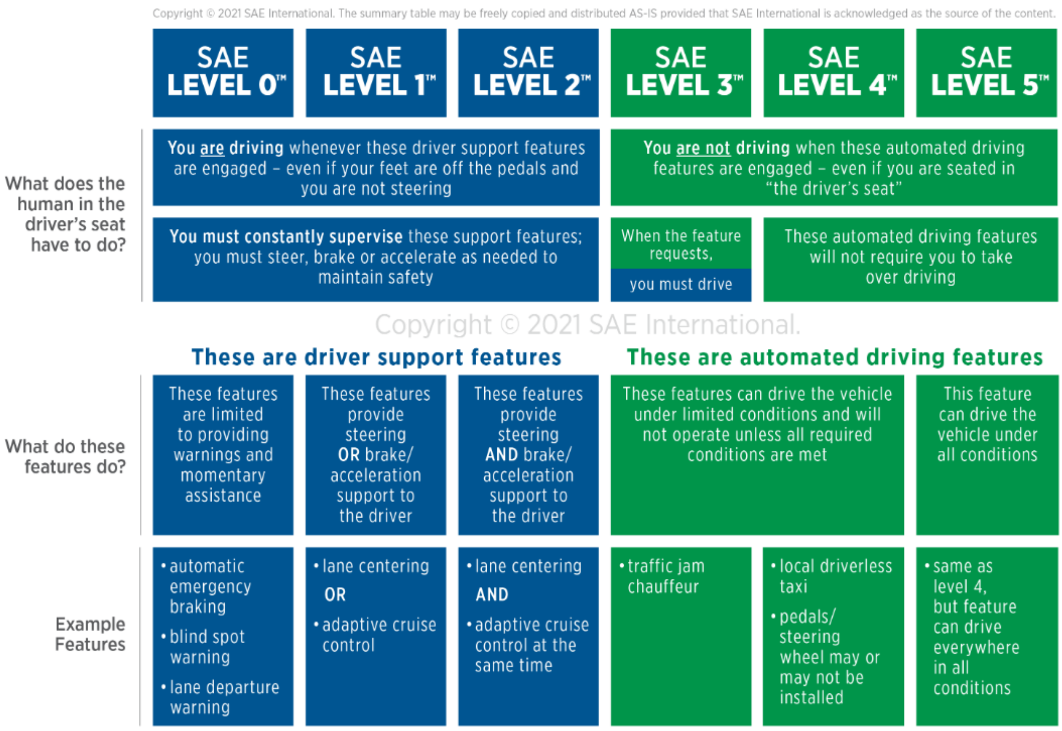

Figure 1.8 SAE's (2021) structure for levels of automation

The first evident difference between SAE's (2021) taxonomy and Parasuraman et al.'s (2000) is that the SAE levels are divided into two groups: driver support features (levels 0-2) and automated driving features (levels 3-5), as the latter fundamentally change drivers' interaction with the driving task. For driver support features, the driver may be relieved from the physical control of many aspects of the driving task (depending of the level of the automation), but they are still responsible for the supervisory control of the driving task, and for a potential intervention in the automation's operation, e.g. in case a system limitation is reached. In that sense, drivers are still required to monitor the vehicle and driving environment, and allocate visual attention to relevant sources of information, for both tactical and strategic management of the driving task (being "on the loop", as described by Merat et al., 2019), as they are only relieved of the primarily operational functions of the driving control loop.

As for the automated driving features, as long as the vehicle stays inside its ODD, there is no need for the driver to monitor the environment, when it comes to the tactical-level information, only being responsible for the strategic control of the task (knowing where to go, and how to get there), acting like just another passenger, on the drivers' seat. However, lower levels of vehicle automation (2, 3, 4) can only operate in a discrete set of scenarios, and therefore, the driver is expected to assume control of the vehicle in certain circumstances (NHTSA, 2016). The limitations in automated driving capabilities are particularly problematic for SAE levels 2 and 3 of automation features, as drivers are partially, or totally, removed from the control loop of the driving task, yet they are required to resume full manual control in a short period of time, sometimes with little, or no, notice (see ISO/TR 21959-1:2020), depending on the level of the vehicle automation. Even though level 2 cannot be considered "automated driving", both levels 2 and 3 are transitional states, where the driver is expected to be ready to react to a system limitation, yet may lack the right cognitive resources to do so in a timely manner (ISO/TR 21959-1:2020). It is, then, necessary to understand the human factors issues related to these sorts of interactions between the human supervisor and the driving task.

1.3.2 Supervisory control paradigm and the driving environment

Parasuraman & Sheridan (2005), and Dekker (2005), define the interaction structure between humans and automation as a supervisory control paradigm, which strictly represents the roles of each individual – human and automation – inside the task, based on their capabilities and limitations.

From the perspective of the human operator, which lacks operational precision, but excels in semantically assessing the situation and controlling the goals of the task, the supervisory control can be divided into five steps (see Figure 1.9): 1) offline task planning; 2) programming and system orientation; 3) monitoring of automated system during task execution; 4) interference of the system workflow (in case of a malfunction or limitation); 5) learn with the experience. From the perspective of the automated system, which is capable of fast and accurate task execution, but lacking in strategic planning capabilities, researchers have outlined similar steps for its operational workflow: 1) observation of the environment through sensors; 2) orientation of the scenario according to the relevant thresholds; 3) decision of the optimal action according to the given scenario; 4) execution of the chosen activity (Young, 2012; Degani, 2004; HSE, 2003; Parasuraman & Sheridan, 2005).

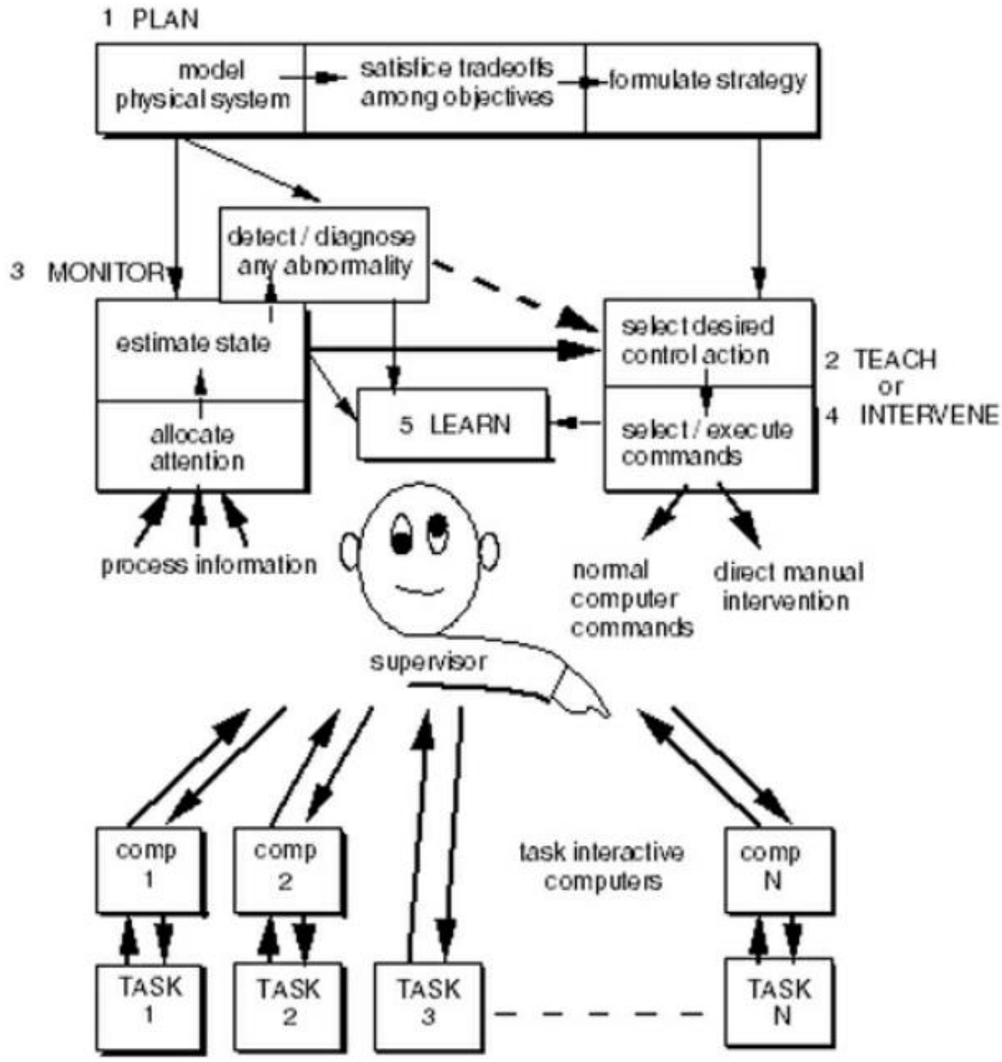

Figure 1.9 Schematic representation of the supervisory control paradigm (Parasuraman & Sheridan, 2005)

Since the human is not actively controlling the driving task, some aspects of driving, such as manually maintaining lane stability lose importance over others, such as having an accurate mental model of the system capability and workflow. Parasuraman et al. (2008) suggests a conceptual framework which assumes that the human interaction with automated systems is primarily mediated by three main constructs: 1) situation awareness, 2) workload, and 3) trust.

Situation awareness (SA) was first defined by Endsley (1998) 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.” In other words, SA is the capability to observe the environment, and recognize the relevant features to assess the situation, and predict the outcome of the operator/driver’s possible actions. Endsley (1995) divided this construct into three levels (perception, comprehension, and prediction). Empirical, driving simulator, studies have shown a strong link between drivers’ involvement in the control loop of an automated vehicle, their situation awareness, and the safety outcomes of potential takeover scenarios (see Louw et al., 2017).

Trust is a construct related to humans' acceptance of the different range of activities performed by the system. According to Lee and See (2004), trust guides reliance of the operator in automation, whenever they do not have the knowledge or certainty of the future outcomes of the system. When it comes to supervision, and transitions of control in automation, Chancey et al. (2015) define trust in automated systems as a mediating factor between fallibility of a given system and the non-interference of its operator. In other words, trust in automation defines how willing we are to put ourselves in a vulnerable position, in the hands of an agent (automation), the behaviour of which we are not certain about. Young (2012) suggests that this element of automation is deeply related to the degree of human vigilance over the task, once it affects how much someone is willing to expose themselves to a possible risk scenario. An excess of trust can lead to complacency in an otherwise vigilant driver (or indeed driver distraction), and under-trust can lead to a stress of drivers’ mental workload (Parasuraman et al., 2008).

Workload can be defined as the disposal of human cognitive and physical effort necessary to achieve the task’s goals. One factor that is particularly unique for the human interaction with automated driving is that drivers must be vigilant (at least in level 2) for both the system workflow and the road environment. As presented above, even though there is no physical interaction with the driving task, the visual search activities related to tactical information/actions (as defined in Merat et al., 2019) is still necessary. Research suggests that this overload of information processing may be detrimental for the human's capabilities to take over (Young, 2012). On the other hand, the lack of physical interaction with the driving task can also lead to an underload of driver's resources, which may lead to boredom, fatigue, and distraction, which are also detrimental for the monitoring task and can increase human error either leading up to, or after a takeover (Parasuraman & Manzey, 2010).

1.3.3 Human factors Issues with automated vehicles

Parasuraman et al. (2008) suggests that inappropriate levels of Situation Awareness, trust, or workload can lead to issues in the interaction with automation. Furthermore, Young (2012) proposed a list of the most common issues that drivers' may face, when interacting with vehicle automation.

Parasuraman & Manzey (2010) suggest that operators of an automated system (driver) regularly allocate cognitive resources away from their monitoring role, under the assumption that the system is reliable and does not fail. This "complacency" by the operator (Parasuraman & Manzey, 2010), is generally linked to well-performing systems, which creates and excessive trust, and is also induced by a lack of workload due to the absence of physical engagement, as for instance, what we can see with the driving task. According to Carsten et al. (2012), in order to relieve boredom, drivers are likely to engage in non-driving related activities (NDRAs) or secondary tasks, when using higher levels of vehicle automation (SAE level 2, or above). This likely interaction with secondary tasks takes drivers' eyes off the road, and can reduce their situation awareness, increasing their crash probability, if a transition of control is required due to system limitations or failures (Zeeb et al., 2015; Louw & Merat, 2017; Damböck et al., 2013).

Parasuraman & Manzey (2010) have also identified "misuses of automation",which, is defined as interaction of an automated system outside its scope of desired use. For instance, due to a lack of trust and knowledge about the system, an operator (driver) may over-commit on their vigilance task. Consequentially, this operator may end up overloading their cognitive resources, leading to an impairment on their performance, in a transition of control. Whenever trust in automation is not an issue, but rather a good understanding of the system, Victor et al. (2018) observed in their experiments that some drivers correctly observed the potential threat, and despite reporting adequate levels of trust in the system, decided (wrongly) not to react to a critical situation. According to the authors, it was caused by an expectation mismatch, as drivers did not have the appropriate mental model of the system behaviour, and therefore made the wrong decision about whether or not to intervene, despite having enough resources to do so.

Another very common problem related to the interaction of drivers with vehicle automation is skill degradation (Young, 2012) where due to the lack of interaction with the driving task, some drivers might have their driver-related skills degraded with prolonged usage of automation. Prolonged usage of vehicle automation, and continuous misuses of safety features may also lead to undesired behavioural adaptations (Rudin-Brown & Jamson, 2013). In that sense, as the drivers gain experience with the limitations of an automated vehicle, they are likely to adapt their behaviour (in a complacent manner, Parasuraman & Manzey, 2010), to overcome potential inconveniences on the interaction, such as expected false alarms of the system. This may end up exposing drivers to unforeseen risks, as they push the boundaries of the safety limitations of the automated vehicle.

At last, one of the most discussed issues related to the interaction between drivers and vehicle automation is the removal of the driver from the decision-action loop of the driving task (Merat et al., 2019). As said before, drivers require a series of information that are being constantly processed to perform the driving task, however, as observed by Louw & Merat (2017), the removal of the driver from the control loop alters the way they process information, and therefore, compromises their situation awareness (out of the loop syndrome, or OotL, Merat et al., 2019). Not only this, but the removal of the driver from the motor control of the vehicle, interrupts their visuomotor coordination (Mole et al., 2019), which may lead to a delay in the stabilization of the vehicle control, after a transition (for examples, see Blommer et al., 2017; Merat et al., 2014).

1.3.4 Drivers' gaze during automated drive

In the previous section of this chapter, it was raised the argument that visual attention patterns are highly dependent of the task in hand (Borji & Itti, 2013). Also, the evidence provided on previous sections suggested that the inclusion of automation in the driving task completely alters its nature (SAE, 2021). With those arguments in mind, when it comes to gaze patterns in a vehicle automation environment, it is necessary to consider the main differences of a manual driving task and automation supervision task, and understand how each of those differences may lead to distinct gaze behaviour patterns.

The first difference to be noted, is that drivers are more likely to engage in non-driving-related secondary tasks, when supervising an automated driving task (as reported by Carsten et al., 2012). Therefore, even for Level 2 system, the proportion of deliberate off road glances (as defined by Trick & Enns, 2009), is likely to increase when automation is engaged, due to drivers' interaction with peripheral devices, such as smartphones, radio, or in-vehicle infotainment systems. Morando et al. (2020, 2021) provide empirical evidence for this assumption, using results from a naturalistic study with Tesla drivers, and show increased visual inattention (longer and more frequent off-road glances) during the automated mode, when compared to manual driving. These authors also report that drivers tend to start deviating their glances away from the road, as soon as they disengage manual control of the driving task.

Another relevant factor that should be considered to this discussion is that drivers should maintain attention to multiple sources of information at once. As reported by Endsley (2006), operators of an automated system (drivers) should be aware not only about the status of the system, but also about the situation of the task that is being performed by the automation (in the context addressed by this research, drive). Considering the fact that most of the system related information is provided by the system's user interface (Goncalves et al., 2017), and the information about the driving task is generally obtained by looking towards the road environment (Horswill & McKenna, 2004), it is to be expected that drivers of an automated system would need to disperse their gaze between the two locations, and constantly shift their attention to maintain situation awareness.

When it comes to gaze dispersion, it is a well-known that drivers tend to look towards where they steer (Land & Lee, 1994). However, simulator studies (Mars & Navarro, 2012; Mackenzie & Harris, 2015) have found that the lack of need for the driver to physically control the driving task increased their average gaze dispersion during curve negotiations. Their findings suggest that without appropriate visuo-motor calibration, drivers tend to reduce the frequency of their guiding fixations (as defined by Lappi & Mole, 2018), and perform more deliberated or exploratory gaze routines of the road environment (either to gather tactical information about their surroundings, or due to driver distraction/boredom). As a complementary finding, Louw & Merat (2017) found that whenever removed from the loop of the driving task, drivers have an overall increase in their gaze dispersion around the vehicle, in an erratic pattern. The authors associated this phenomenon with lower levels of situation awareness, caused by a lack of demand for interaction/vigilance of the driving task. That said, we can consider that a lesser involvement (both physically or tactically) with the driving tasks makes drivers prone to bottom-up saliences of attention, since there is no real demand for a structured deliberated gaze scanning routine.

1.4 Human factors of the transitions of control

As highlighted in the previous subchapter, for some levels of vehicle automation (especially Levels 2 and 3), the automated system is not able to operate in all driving and road environments, or may fail unexpectedly, therefore requiring the human to resume control of the driving task, in a timely, and safe, manner (NHTSA, 2016). However, as stated by Merat et al. (2019), and Mole et al. (2019), the removal of the driver from the active role of driving makes it difficult for them to quickly, and efficiently, re-insert themselves back into the decision-making and control loops, (ISO/TR 21959-1:2020). According to Seppelt & Victor (2018), achieving a safe transition of control in a timely manner, is one of the most prominent human factors challenges for current systems, which has captured the attention of many researchers over the past 10 or so years. This challenge is associated with a mismatch between the amount of information necessary required by the driver for a safe transition of control, and their information processing capabilities (as reported by Goodrich & Boer, 2003). This subchapter will discuss the nature of the process of transition of control from driving automation; its challenges; influencing factors; and how gaze behaviour and visual attention is related to this process.

1.4.1 Transition of control definition

The process of partially/totally relinquishing or assuming control of an automated vehicle is commonly referred to as a “transition of control”. In his work, Louw (2017) defined a transition of control 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.” (Louw, 2017, p.12). Of course, a transition is not always extreme or critical (i.e. from no motor/supervisory control to full control), nor is it unilateral. Flemisch et al. (2008), and Martens et al. (2007) developed taxonomies for the process of transition of control, which were further structured in the ISO regulation TR 21959-1:2020 (see ISO/TR 21959-1:2020). The taxonomy proposed by ISO considers three main factors that define three elements of a transition:1) the initiator of the transition process, 2) the direction of the transition, and 3) whether or not it was a deliberate, or forced action.

When it comes to the **initiator** of the transition, the event can be either system initiated, or driver initiated. The **direction** can be up/higher or down/lower, between full manual control (Level 0) and Levels 1, 2, or 3 (and any in between). The third aspect, relates to **urgency**, which, as the name suggests, defines whether this is a forced transition (where the driver/system does not have the option to ignore the request without a major safety implication), or optional, where the absence of action will not disturb the current state of the driving task, but the drivers wishes to resume control, for other reasons.

The research developed in this document, focuses on system-initiated transitions between SAE Level 2 and 3 to Level 0. These are deliberate/forced transitions of control to both critical and non-critical, following a request to intervene (as can be seen in Figure 1.10).

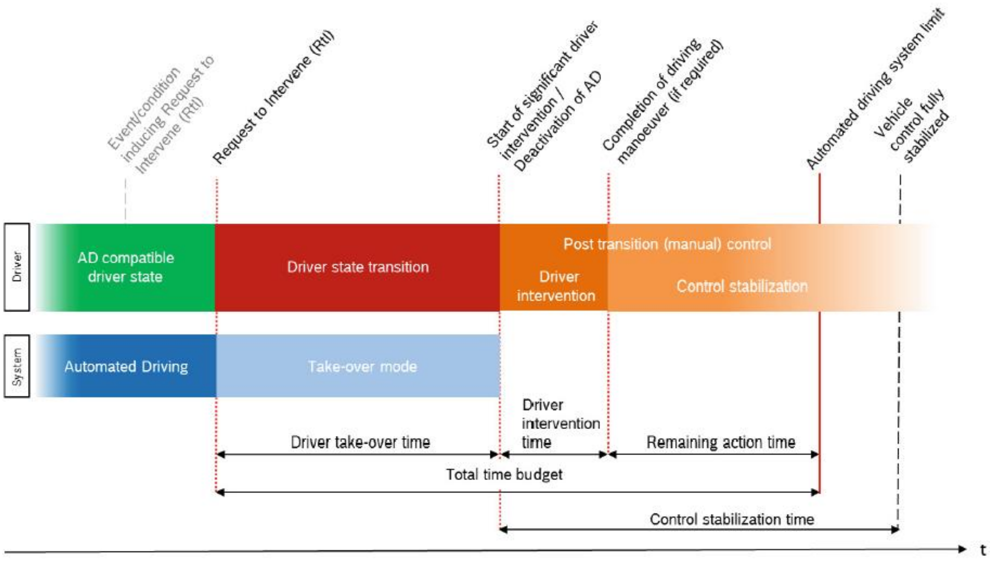

Figure 1.10 ISO/TR 21959-1:2000's representation of system initiated transition from automated to manual driving (ISO/TR 21959-1:2000)

As shown in Figure 1.10, the transition of control is a process with many steps. The process starts with a supposedly unready driver, who receives a **takeover request**, in the case of an L3 system, or perceives the need to takeover, in the case of an L2 system. Once the need is understood, the driver passes through a **transition state**, where they will gather information about the system and road environment, until they deactivate automation and recover manual control of the vehicle. Once in manual control of the vehicle, the driver will still need to **stabilise the control**, as they recover their visuomotor coordination, and scan the situation, to assure the transition was successful.

Takeover Requests (applicable specifically for L3 systems) or TOR, can be defined as a system-initiated alarm to invite the driver of an autonomous/automated vehicle to resume one or both lateral or longitudinal control of the driving task (Melcher et al., 2015).

The transition state, as defined by ISO, is the moment where drivers engage in visual scan activities, to recover both situation awareness (as described by Gartenberg, 2014) and visuomotor coordination (as described in Mole et al., 2019), until they are sufficiently re-inserted in the control loop, and able to manually assume control of the situation (Merat et al., 2019). The **stabilization** period is caused by any potential inadequacies in their re-insertion in the control loop of the task (as reported by Merat et al., 2014;

Louw et al., 2018; and Blommer et al., 2017), which is generally characterized by minor motor control adjustments, to regulate steering and speeding calibration, as well as quick glances towards the vehicle's cluster and surroundings (as observed by Tivesten et al., 2015).

1.4.2 Transition of control requirements

The arguments presented above suggest that, during the state transition phase, drivers need to gather the right (and right amount of), information to be re-inserted in the decision-making and control loops necessary to safely drive a vehicle (ISO/TR 21959-1:2000). It is now necessary to discuss which kind of resources are needed to recover control of a vehicle, based on Michon's (1985) model, considering the driving task as a constant loop of information processing (Hollangel & Woods, 1995).

When defining the concept of Out of the Loop, caused by the continuous exposure of the driver to vehicular automation, Merat et al. (2019) stated that the "loop" could be divided into two: "(…) we suggest that "being in the loop" can be understood in terms of (1) the driver's physical control of the vehicle, and (2) monitoring the current driving situation (…)" (Merat et al., 2019). In short, Merat et al. (2019) proposed that the "loop" of driving a vehicle is divided in two distinct subroutines: 1) a motor control loop physical interaction with the vehicle's movement control and 2) a decision-making loop, related to strategic and tactical information processing (as defined by Michon, 1985).

Given the structure of transitions of control described above, it is to be expected that a forced transition to manual (from L2/3 to 0) is needed due to a system limitation, or critical event, that requires precise and timely human intervention, since the automated system is unable to handle the situation accordingly. With that, driers will need to have adequate levels of involvement in both decision-making and motor control loops, to safely respond to the demands of the task.

Considering the definition above, one can assume that a transition of control can be interpreted as a decision-making problem. In this perspective, a situation is presented to the decision-maker (driver), which will need to look for information and ponder, from a myriad of possible options, what is the adequate solution. Authors such as Merat et al. (2019) have suggested that this decision process is tightly related to the process of situation awareness recovery, and to the three levels of situation awareness:

- **Level 1 – Perception**: Drivers should be able to notice the need for an intervention, by either receiving a TOR (in case of L3 systems) or noticing cases of system limitations (in case of L2 systems).
- **Level 2 – Comprehension**: once perceived the need to takeover, driers should look for strategic-level (as defined by Michon, 1985) information on both the system and environment, to understand the current state of the environment and why an intervention is needed.
- **Level 3 – Projection**: After understanding the situation, a myriad of possible solutions will be pondered, and manoeuvring-level information (Michon, 1985) will be processed, to define what is the most adequate solution to the problem in hand.

After the decision process is made, drivers are ready to assume the motor control of the vehicle. However, they still need process control level information, to resume a stable control of the driving task.

When it comes to the **decision-making loop**, many authors in the field of human factors in vehicle automation (Louw & Merat, 2017; Zeeb et al., 2015; Eriksson & Stanton, 2017), and on basic human-automation interaction (Endsley, 2006/1995; Parasuraman et al., 2000; Sheridan & Parasuraman, 2005) have demonstrated that prolonged interaction with automation may lead to a loss of situation awareness (as defined by Endsley, 1995). Endsley (1995) described the third level of situation awareness as the ability of an individual to make sense of the information in hand, to project future scenarios. With that in mind, one can assume that situation awareness is a core element of the decision-making loop (Merat et al., 2019), because, in order for drivers to manage a situation upon receiving a TOR, they need be able to avoid potential hazards, and handle any unexpected outcomes of their actions.

When it comes to re-acquiring situation awareness, drivers follow a visual scanning procedure, called "situation awareness recovery", or SAR (Gartenberg, 2014). This process is composed of quick and dispersed samples towards both the road environment and vehicle’s automated systems (via a range of Human Machine Interfaces). Gartenberg (2014) also reported that this process has a high ratio of attention refocused in different sources of information, due to the eccentricity of the visual scanning process (Gartenberg, 2014). The SAR theory is based on the Memory for Goals model (Altmann & Trafton, 2002), which assumes that the focus of the attention required to recover situation awareness is based on drivers’ current stored information in their short-term memory, regarding the situation in hand. According to Endsley (2006), the operators (drivers) of an automated system follow a goal-directed, top-down, structure, when recovering situation awareness, shifting their attention to places they believe (based on their experience) are likely to provide the information needed to complete their mental model of the situation, and achieve their goals.

The **motor control loop** is tightly related to visuo-motor coordination (Wilkie & Wann, 2010). In an extensive literature review, Mole et al. (2019) suggest that the interruption of the physical control of the driving task compromises the calibration between drivers' motor control inputs and their visual perception of locomotion, jeopardising their ability to perform a stable driving task, after resuming control of the vehicle (as seen in Merat et al., 2014; Blommer et al., 2017). According to Mole et al. (2019), to recover such calibration, drivers rely on the optic flow of the scenery in their field of view, giving them the notion of movement and control of speed (see Okafuji et al., 2015), as well as guiding fixations, either to the centre of the road, or towards where the driver wishes to steer (see Wilkie & Wann, 2010).

1.4.3 Challenges for a good transition of control

As outlined above, the process of transitioning control from vehicle automation can be challenging, with a large volume of information to be processed by drivers, sometimes in a limited amount of time. According to Eriksson & Stanton (2017), depending on the situation, drivers may take between 5 and 30 seconds to recover sufficient resources to resume control of automation. Complementary research from Merat et al. (2014) shows that, even after resuming manual control of the task, the driver may take up to 40 seconds to stabilise the vehicle's position in the road, to match the control seen in manual driving before automation was engaged. Endsley & Kiris (1995) list a series of inherent challenges to the process of recovering control of an automated task, associated with human limitations, in terms of information processing, and attention switches. It is now important to consider the constraints inherent to the transition of control from vehicle automation that might cause delays in drivers' response, and therefore, reduce safety.

In his studies, Wickens (2008) concluded that humans are not especially good at attending to multiple workload demands at the same time, due to limitations on their working memory and processing capabilities, since each information needs to be processed procedurally. This issue is evident in the field of automation (Parasuraman & Rilley, 1998) and especially in the field of transitions of control in vehicle automation, where it was been shown that time pressure or information overload might affect the quality of drivers' decision-making (Gold et al., 2013). The field of decision-making theory address a similar problem with the concept called bounded rationality (see Simon, 1972 for a more detailed definition), which describes the lack of capabilities for an individual to process all the information they have in hand, making them unable to achieve an entirely rational decision, the more pressure/demand is imposed before the decision-making.

The arguments above show that bounded rationality constantly constraints drivers during a transition of control. For this reason, drivers will need to deal with uncertainty, assuming that it is likely that they won't have time to sample all the information they would ideally need to make a fully-rational (see Edwards, 1954 for a review of the term) decision and reaction. In those cases, drivers might have to prioritise certain visual information over others to perform a transition of control (for more details about this process, see Goodrich & Boer, 2003).

1.4.4 Factors influencing driver behaviour during transitions of control

If it is assumed that the transition of control from automation is akin to a risky decision-making process, it is feasible to presume that several factors can affect the difficulty of this decision, and therefore influence drivers' takeover time and the quality of a transition. This section presents evidence from the literature about the most relevant factors influencing human performance in transitions of control in vehicle automation.

For critical transitions of control, a **time budget** is provided between the time a takeover request (TOR) is issued by the system (or in case of a driver initiated takeover, from the perception of the potential issue), until the moment when a crash is unavoidable. The time budget has a direct influence on drivers' takeover performance, since it dictates how much information they can process, before executing a takeover manoeuvre. Reports from Gold et al. (2013) and Damböck et al. (2013) suggest that shorter time budgets directly influenced drivers' capabilities to avoid a crash in a takeover scenario, as well as how they distributed their gaze across the environment.

For example, Gold et al. (2013) showed that as the time budget decreased (7s to 5s), drivers had a lower probability to sample the road environment, such as reduced use of the side mirrors, which also affected their subsequent reaction (where brakes were more frequent, when trying to avoid a hazard, compared to braking and steering). Xu et al. (2022) also demonstrate that drivers with a lower time budget to takeover had a lower number of look- ahead fixations across the environment, and focused more on the road centre, suggesting the drivers with limited resources opted to focus on the manoeuvre to be performed, instead of looking to obtain additional situation awareness. However, When it comes to longer time budgets, it is possible that a flooring effect can be perceived on drivers' performance. Louw et al. (2018) demonstrated with a multilinear regression analysis that drivers' response time was not predicted by the time budget of the event they drove, but rather by the kinematics of the scenario. The overall takeaway for the researchers is that if you give more time for drivers to react, they are more likely to use it, and only actually respond when the situation approaches alarming levels of criticality.

Another factor that mediates performance and reaction time during transitions of control is **drivers' levels of situation awareness/ involvement with the loop** prior the takeover request. The same way time budget constrains drivers' capabilities to process all the necessary information to perform a rational decision to takeover, the amount of cognitive resources (in this case, situation awareness) needed to be gathered for such rational decision is also a constraint for drivers' takeover capabilities. Zeeb et al. (2015/2016) have demonstrated that drivers who spent time looking away from the road centre in vehicle automation (likely performing secondary tasks) presented longer takeover times and higher crash probabilities in driving simulator experiments. The explanation behind such results is the assumption that, once the drivers were less aware about their surroundings, they needed more time to gather all the information they needed.

When it comes to eye movements and the involvement of the driver with the loop, Louw & Merat (2017) showed that despite the fact that the more drivers are removed from the loop, the more likely they are to crash in a critical takeover, individual differences on their eye movements after the TOR quickly disappear in the first few seconds of the transition process. The rationale behind this observed behaviour is the fact that their attention is immediately attracted to the threat ahead, as they make sense of the surrounding environment. It is still important to consider that drivers with lower levels of situation awareness are still required to sample for more information on the environment, to achieve similar performance results, when compared to drivers who were attentive to the environment, while the automation was on.

Another factor that may affect the outcomes of the transition process is how well/quickly the driver can gather the information at their disposal. Therefore, one can assume that the usage of advanced **human machine interface** (HMI) solutions may help the drivers' with pre-processed information to support their decision about when and how to resume control. When it comes to the understanding of the status of the automated system, Banks & Stanton, (2016) Saffarian et al., (2012), and Stockert et al. (2015) showed that the HMI of the vehicle increased drivers' perceived levels of trust, and comprehension of the system behaviour. On the other hand, automated vehicles that presented supportive information regarding the road environment (see Richardson et al., 2018; Naujoks., 2017) presented reduced response times in transition of control scenarios. This finding leads to the assumption that the information about the surrounding environment can more efficiently interpreted by the driver, when pre-processed by the sensors of the vehicle during a transition of control.

At last, again considering the transition of control process as a risky decision-making, we can assume that the more complex the **surrounding environment**, the more uncertainty (see Shaw, 1982 for the definition of the term) would be associated with the decision process, and therefore, compromise drivers' performance. As presented above, Louw et al.'s (2018) study showed that drivers do not tend to react to time budgets (the more time you give, the longer the drivers will get to respond), but rather to the evolving criticality of the situation, as they are approaching the collision to the lead. In the same perspective, Xue et al. (2019) developed a drift diffusion model to predict drivers' brake response to a forward collision warning, concluding that their response is generally based on the looming obstacle ahead.

1.4.5 Gaze and decision during transitions of control

The sections above presented the idea that the process of re-insertion of the driver into the decision-making and control loops can be challenging, due to constraints on humans' limitations in information processing capabilities

(Endsley & Kiris, 1995). Therefore, drivers generally do not have time to recover the ideal amounts of situation awareness and visuomotor coordination whenever a transition of control is requested. According to Edwards (1954), when a decision-maker (driver) is forced to decide without the whole notion of the parameters that affect the outcomes of their choice, this decision is not entirely rational and is made based on risk models, where the outcome of their actions cannot be predicted, but instead estimated. Examples of such decision-making structures can be seen in Boer & Goodrich (2003). They state that drivers generally apply a satisficing decision-making approach rather than what they would judge to be ideal. The most relevant characteristic of risky decision-making is that they are consistently biased by several factors, such as the arbitrary, selective attendance of the decision-maker to a particular set of information, over others.

According to Orquin & Loose (2013), visual attention and decision-making are tightly coupled in a way that risky decision-making is continuously biased by the attendance/non-attendance to relevant visual information available to the decision-maker. In their literature review, the authors were able to find a co-causal relationship between visual attendance to information and the occurrence of specific decision choices, in a discrete decision-making scenario. The authors analysed several publications on the field of decision-making theory that used eye-tracking data as a dependent variable and concluded through a meta-analytical approach that the fixation of the individual's gaze on certain key information can be a predictor of their upcoming choice in a discrete scenario, as a co-causal factor. Based on this study, it is possible to argue that the selective attention of drivers may bias their decision-making. Such approach may also be applied to analyse drivers' response capabilities in a take-over scenario, once a take-over reaction is nothing more than a selective response to a certain environmental condition, where drivers need to acquire multiple information in order to respond accordingly and in a timely manner.

1.5 Summary and key research gaps

The literature review presented in the previous sections demonstrates that drivers' visual attention selection patterns are dependent on a series of contextual factors, such as the involvement of the driver in the loop (e.g. Louw et al., 2016; Zeeb et al., 2016), and scenario kinematics (e.g. Gold et al., 2013). On the other hand, It was observed that some aspects of gaze could be correlated with the safety outcome of a transition of control (see Louw et al., 2016; Svaard et al., 2022).

If the process of transition of control is biased by selective attention allocation and task conditions bias visual attention allocation, it is reasonable to assume that different take-over scenarios and visual attention allocation patterns will yield different take-over responses. On the other hand, It is not yet clear how information available to the driver in a vehicle automation scenario, once sampled, may affect the drivers’ takeover process, nor how the impact of the situation in which the transition of control was issued affects drivers’ visual attention allocation. Based on the arguments above, two main research gaps can be outlined about how drivers acquire and use visual information on their surroundings to perform a transition of control in vehicle automation:

- The lack of dedicated studies in the literature that systematically manipulate attentional demands, focused on understanding how they affect the structure (top-down and bottom-up) of drivers’ gaze patterns. Examples of such demands are: drivers' involvement with the decision-making and control loops of the driving task, and the presence of HMI information to support the transition process. While studies such as Gold et al. (2013), Richardson et al. (2018), and Zeeb et al. (2016) did manipulate the situation kinematics, the presence of supportive HMI and the involvement of the driver in the loop, respectively, their studies were not focussed on how those manipulations affected drivers gaze during the transition process.

- There is a lack of a mechanistic explanation about how drivers use visual information to perform a transition of control. Even though Louw et al. (2016) had shown a probabilistic correlation between drivers' performance during a transition of control and the pattern of drivers’ visual attention allocation, it does not provide us with any insights on how this information was used to perform the action, nor explains internal variability across the different trials in their experiments. On the other hand, gaze-based decision-making models (e.g. Krajbich et al., 2012) were able to explain the value of distinct information sources on the individuals' decision process, but they were not tailored considering the specificities of the process of transition of control (such as the process of situation awareness recovery, and visuomotor coordination).

1.6 Research question and objectives

1.6.1 Research goal

Based on the research gaps presented above, this research assessed drivers' decision-making responses to transitions of control from vehicle automation, based on the way they sample visual information available in their field of view. This research also investigated how the involvement of the driver on the decision-making and control loops; characteristics of the surrounding environment and the presence of system-provided information affect the way drivers allocate their gaze to decide how to transition control from automation.

1.6.2 Research questions

- How competing demands of visual information are prioritized during drivers' transition of control from vehicle automation?
  - What is the effect of drivers' engagement in the motor control and cognitive loops of the driving task on their visual attention allocation patterns during transitions of control from vehicle automation?
  - How does the type of information presented on the HMI of an automated system affect drivers' gaze behaviour during transitions of control from vehicle automation?
  - How the scenario kinematics affect drivers' gaze behaviour during transitions of control from vehicle automation?
- How drivers' visual attention allocation patterns can be correlated with drivers' decision to transition control from vehicle automation?
  - What can be considered a safe gaze behaviour pattern for transitions of control?

To answer the purposed research questions, this research will use data previously collected from driving simulator experiments conducted on the University of Leeds Driving Simulator (UoLDS). All the data was processed post-hoc, and the research questions described in this document were not considered during the initial planning of the original studies. This approach is a cost-efficient way to tackle the research problem, as it provides a large variety of scenarios to be observed, without restricting the research to a particular situation.

Over the course of the research project, the experiments analysed varied in terms of eye-tracking technology used for data collection. With that in mind, one should note that the metrics may not be consistent across the chapters of this thesis. Also, as the research progressed, new techniques and analysis methods were learned, and applied in different chapters of the thesis. The reader should take into account that, due to the reasons mentioned above, the data and methods presented in different chapters are not fully comparable. On the other hand, the findings and implications of the research methods may complement each other. A consideration about how all the techniques applied across chapters answer the research questions will be present in the conclusion chapter of the thesis.

1.6.3 Thesis overview

As outlined in Figure 1.11, the overall structure of the study takes the form of eight chapters.

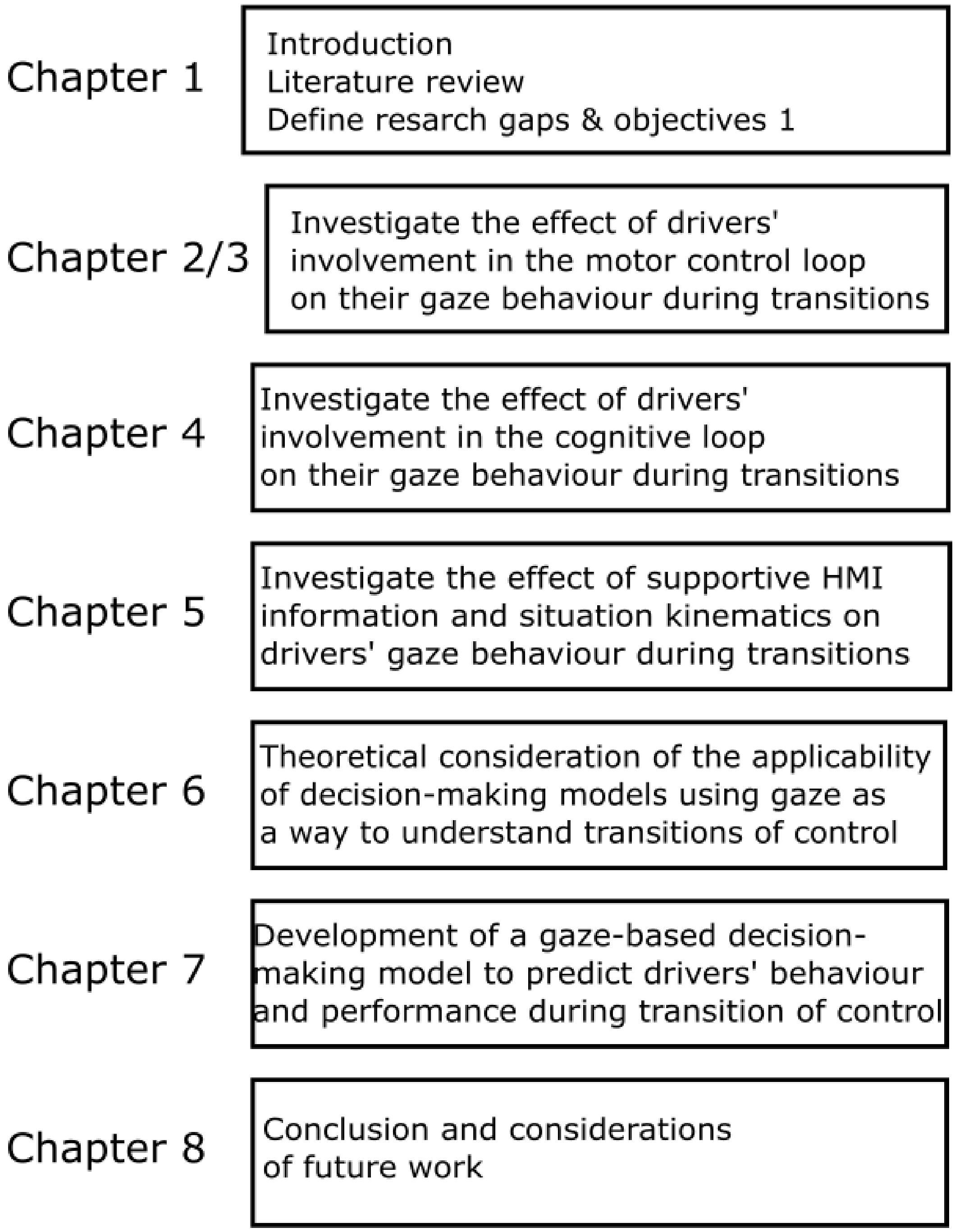

Figure 1.11 Thesis chapter structure

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2.
The Effect of Motor Control Requirements on Drivers' Eye-Gaze Pattern During Automated Driving

Abstract

This driving simulator study compared drivers' eye movements during a series of lane-changes, which required different levels of motor control for their execution. Participants completed 12 lane-changing manoeuvres in three drives, categorised by degree of manual engagement with the driving task: Fully Manual Drive, Manual Intervention Required, Fully Automated Drive (Manual drive, Partial automation, Full automation). For Partial automation, drivers resumed control from the automated system and changed lane manually. For Full automation, the automated system managed the lane change, but participants initiated the manoeuvre by pulling the indicator lever. Results were compared to the Manual drive condition, where drivers controlled the vehicle at all times. For each driving condition, lane changing was initiated by drivers, at their discretion, in response to a slow-moving lead vehicle, which entered their lane. Failure to change lane did not result in a collision. To understand how different motor control requirements affected driver visual attention, eye movements to the road centre, and drivers' vertical and horizontal gaze dispersion were compared during different stages of the lane change manoeuvre, for the three drives. Results showed that drivers' attention to the road centre was generally lower for drives with less motor control requirements, especially when they were not engaged in the lane change process. However, as drivers moved closer to the lead vehicle, and prepared to change lane, the pattern of eye movements to the road centre converged, regardless of whether drivers were responsible for the manual control of the lane change. While there were no significant differences in horizontal gaze dispersion between the three drives, vertical dispersion for the two levels of automation was quite different, with higher dispersion during Partial automation, which was due to a higher reliance on the HMI placed in the centre console.

2.1 Introduction

The motivation for this study comes from a well-known challenge in the field of Human Factors in Transportation, which is that the introduction of vehicle automation to the driving task can remove drivers' involvement in the decision-making and control loops (Louw and Merat, 2017), and this removal may ultimately compromise drivers’ capabilities to make decisions, and act appropriately, whenever their intervention for system control is required (Young, 2012). Due to their limited Operational Design Domain (ODD), some vehicles are unable to perform certain complex manoeuvres, which involve decision-making elements, such as changing lane on a busy motorway. Therefore, some authors have argued that, in these situations, drivers might need to re-acquire sufficient situation awareness (Endsley, 1995) in order to safely and accurately resume control from the system, and accomplish the desired task or manoeuvre (see e.g. Louw and Merat, 2017; Zeeb et al., 2015; Dambock et al., 2013).

According to Gartenberg et al. (2014), the process of situation awareness recovery relies heavily on visual search, where the automation’s operator (a driver in the context of this research) distributes their visual attention between relevant sources of information, to create the right mental model, in a goal-directed approach, for the correct execution of a given task. In the context of the information processing required for driving a vehicle, Sivak (1996) has also stated that this is mainly a visual task, that is achieved via tight coordination with the drivers’ motor control systems, allowing them to guide the vehicle in the right direction, at the desired speed. The links between gaze-based measures, attention to, and successful completion of, tasks have been established for some time in studies on human behaviour. For example, Carrasco (2011) and Posner (1980) demonstrated that longer fixation durations towards one specific point of interest are a good indicator of where drivers are placing their attention. However, drivers’ visual attention is also known to vary depending on the scenario in hand (Borji & Itti, 2013), and can also change based on the different demands imposed by the driving environment (Crundall et al., 2003). In a similar line of thought, Sullivan et al. (2012) demonstrated through a simulated driving task that drivers had increased gaze time and frequency towards a particular information source while under conditions of higher levels of uncertainty. In that sense, it is to be expected that drivers, whenever recovering control of the vehicle (assuming low levels of situation awareness), are more likely to gaze longer and more frequently towards the areas which they expect to find the most relevant information. For example, Salvucci, Liu & Boer (2001) have demonstrated that drivers' gaze during a lane change task is generally characterised by an increased number of fixations towards the side mirrors, followed by a concentration of gaze towards the vehicle's heading - the destination lane.

In terms of lane-changing behaviour, Tijerina et al. (2005) report on two distinct phases of eye-tracking patterns. Defining a lane change as "(…) a deliberate and substantial shift in the lateral position of a vehicle with the intent to cross a lane boundary to enter an adjacent lane (…)", these authors link eye movement patterns to two main phases of the lane changing manoeuvre. The first phase, which occurs prior to the manoeuvre itself, is characterised by the acquisition of safety-related information, allowing the driver to decide if it is safe to overtake. Examples of such safety-related information include gap acceptance, the relative speed of their vehicle, distance to the vehicle ahead, and distance to the designated location in the adjacent lane (Gipps, 1986; Zheng, 2014). In terms of eye movements, Tirjerina et al. (2005), and Doshi & Trivedi (2009) report that this phase is generally characterised by a high frequency of glances to the mirrors, as well as over the shoulder checks. The second phase, on the other hand, termed the execution phase, is extremely demanding in terms of vehicle control and requires drivers to be aware of their vehicles' acceleration, steering control, and relative position on the road (Chovan, 1994). When it comes to eye movements, using results from a naturalistic driving study, Salvucci & Liu (2002) showed that drivers generally shift their primary visual focus from their own lane to the destination lane, immediately after the onset of the lane change. This study also showed a reduction in drivers' attention to the mirrors and road ahead at this stage of the manoeuvre.

On the topic of situation awareness acquisition, Louw et al. (2015) suggest that automated driving reduces situation awareness by taking drivers "out of the loop", with two different loops involved: "(…) we suggest that "being in the loop" can be understood in terms of (1) the driver's physical control of the vehicle, and (2) monitoring the current driving situation (…)" (Merat et al., 2019, p 6.). In this broad view of the problem, drivers are not only required to look towards the road to acquire the right information for appropriate situation awareness, but also need to apply the correct visuomotor control coordination (see Wilkie & Wann, 2010; Mole et al., 2019a), and consider the correct strategic planning of their future actions (Land et al., 2006). Endsley (2006) suggests this as a critical challenge of situation awareness acquisition in automation, where high levels of, spatially dispersed, information might exceed the operators' (drivers') capabilities, limiting their ability to attend to all relevant information, enforcing the prioritisation of certain information, above others.

Following the issues described above, it is of interest for the current state of the art on Human Factors in Automation research to understand if, and how, drivers' gaze behaviour is affected when they relinquish control from the vehicle (which is thought to fundamentally change the context of the task, see Parasuraman et al., 2000). It is also important to establish whether different levels of motor control, as determined by the level of automation, have different effects on this gaze behaviour, and, therefore, drivers' strategies for gaining situation-awareness, and ultimately, safe resumption of vehicle control. In this paper, motor control requirements is defined as the need for drivers' to actively monitor and guide the lateral and longitudinal movement of the vehicle, by interacting with the vehicle controls (cf. Merat et al. 2019). In this sense, it is expected that tasks with higher motor control requirements would demand the driver to coordinate their steering wheel and pedal movements to match their desired goal, based on the visual information acquired from the vehicle's movement (visual-motor coordination, Wilkie & Wann, 2010).

Previous simulator studies, investigating the lack of physical control during the driving task (generally caused by engaging automation) have reported an increased gaze dispersion away from the centre of the road, whenever drivers were not in control of the vehicle (Mars & Navarro, 2012; Mackenzie & Harris, 2015; Louw & Merat, 2017). Such patterns are even seen to be true for highly demanding phases of the driving task, such as curve negotiation. Mole et al. (2019a) suggest this change in gaze behaviour can be problematic since the interruption of the perceptual-motor coordination used in tasks such as driving can reduce the association between drivers' eye fixations and the vehicle's heading, which can reduce safety if automation fails (see also Mole et al. 2019b).

However, according to Mars and Navarro (2012), drivers' gaze behaviour pattern during curve negotiations in automation does not change significantly, compared to that seen during manual control, with drivers diverting a similar proportion of gaze to the same locations in given periods of time. The authors suggest that the eyes seem to follow the movement of the vehicle's heading, even when drivers are not in manual control, arguing that the placement of drivers' vision is not just affected by the bidirectional coordination between the eye and arm-motor systems, but also by kinematic cues caused by the visual perception of motion. However, an increased dispersion in drivers' gaze was also observed in this study, which, as suggested by Mole et al. (2019a), might affect drivers' ability to resume motor control, whenever required, especially after long periods of automated driving.

For less demanding driving situations, Mackenzie & Harris (2015) observed that drivers not in manual control of the driving task tend to prioritise scanning activities (e.g. looking for hazards in the periphery) over control-related gaze monitoring, such as looking towards vehicle heading. According to these authors, the importance of some information falls in favour of others, when we are not actively in control of the task, since, we as drivers tend to gaze towards what it is important to us.

However, it is important to note that the above studies were conducted in quite simple driving environments, in order to focus specifically on the effect of motor control of the vehicle as a dependent variable. The limitation of such an approach is that it lacks applicability for more complex scenarios, such as automated lane change manoeuvres, which might impose new demands on the driver, leading to a change in gaze behaviour patterns, as suggested by previous literature (see Crundall et al., 2003; Borji & Itti, 2013). Therefore, to understand how different levels of engagement with the control loop affect the way drivers disperse their gaze to acquire situation awareness for a response to a given task, it is necessary to isolate the need for motor control as a dependent variable, but in more complex scenarios, which require higher levels of decision-making that may influence gaze scanning behaviour.

2.2 Current study

This study forms part of a larger research programme related to the EU-funded AdaptIVe project (Grant Agreement No. 610428), the aim of which was to provide a deeper understanding of drivers' behaviour during transitions of control from automation to manual driving. The goal of the current study was to investigate drivers' visual scan patterns during a number of lane changing tasks, which, based on the level of automation engaged, differed in terms of the level of motor control, and decision-making required. It was hypothesised that drivers with different motor control demands would give priority to different kinds of information, such that drivers in active control of the vehicle would focus more on the vehicle's heading. In contrast, drivers without motor control of the task would focus on hazard perception routines, characterised by a higher lateral gaze dispersion during task execution.

2.3 Method

1.3.1 Participants

A total of 30 fully-licenced UK drivers were recruited for this study, using the University of Leeds Driving Simulator (UoLDS) participant database. One person withdrew from the study, and results are, therefore, based on the remaining 29 participants (15 male and 14 female). All participants had at least 2 years' driving experience (M = 13.62, SD = 9.62) and varied in age between 21 and 60 years (M = 34.21, SD = 8.94). Participants received a full set of instructions for the study and were compensated £20 for taking part. The study received approval from the University of Leeds Ethics committee (Reference Number LTTRAN-054) and took just under two hours to complete.

1.3.2 Materials

The experiment was conducted using the University of Leeds Driving Simulator, which consists of a Jaguar S-Type cabin, with fully operational controls, located inside a 4m spherical projection dome, with 300° projection angle and equipped with an 8 degrees of freedom motion system (see Figure 2.1). A Seeing Machines FaceLab eye tracking device (v4.5) was used to record participants' eye movements at 60Hz.

Figure 2.1 University of Leeds Driving Simulator

1.3.3 Design and Procedure

The experiment followed a 3 (automation level) x 12 (lane changing manoeuvre) repeated-measures, within-subjects, design, where all participants had to perform the same task under three different levels of automation condition: Manual drive, Partial automation, and Fully Automated Drive (Full automation). These were presented in a fully counterbalanced order.

The experimental scenario involved travelling on a three-lane motorway, with a speed limit of 70 mph, where automation (if present), was available in the middle lane. There was a regular flow of traffic (70 mph) in lane one of the motorway (to the left of the ego vehicle), and no vehicles in lanes 2 or 3 (see Figure 2.2). For automation to be activated, participants were required to enter the middle lane (lane 2) and maintain the speed limit, while also driving in the centre of the lane. The 80.64 km long road depicted a typical UK motorway, and consisted of straight sections of road, with a few gentle curves (252 m with a 1km radius).

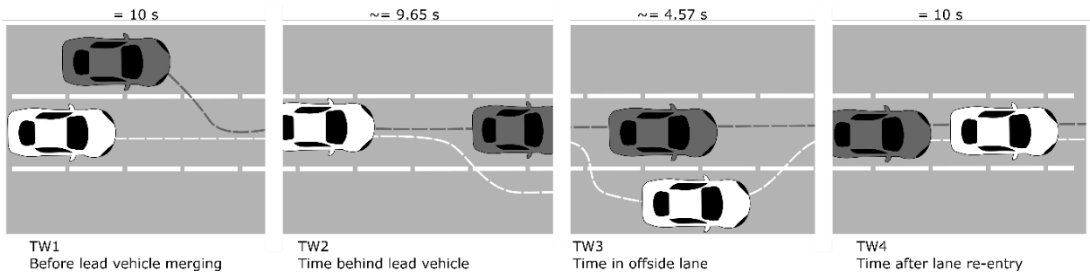

Figure 2.2 Representation of the various phases of the traffic scenario during the Lane Change experiment (Avg. 34.22 seconds duration)

During each of the three drives, 12 events were choreographed, where a vehicle from the left lane (lane 1) entered the middle lane (lane 2) and gently reduced its speed (to around 50 mph), slowing the ego vehicle down and prompting the need for a lane-changing manoeuvre by participants. Here, participants were asked to change lane, if they so wished, and if they did not overtake the lead vehicle, no critical event ensued, and drivers were simply caught behind this slow-moving vehicle. After overtaking the lead vehicle, participants were required to move back into the middle lane, as soon as it was safe to do so and return their speed to 70 mph, in order to reengage the automated system (for the two automated drives).

For the two automated drives, participants were told that they were not required to monitor the environment. They were instructed to only interact with the steering wheel during the manual sections of the drives, or during the take-over situations (whenever required). The Human-Machine Interface (HMI), located in the centre cluster, presented different information related to the behaviour of the system. The HMI was developed in conjunction with CRF (Fiat) as part of the AdaptIVE project (see also Madigan et al., 2018 for further details). Details of the HMI for each driving condition are outlined below:

Manual drive: The driver was entirely in control of the vehicle's lateral and longitudinal position (SAE level 0; SAE, 2018). All the overtaking manoeuvres and vehicle control were performed manually by the participants. In terms of HMI, as automation was not available throughout the manual condition, no automation-related information was displayed (see Figure 2.3).

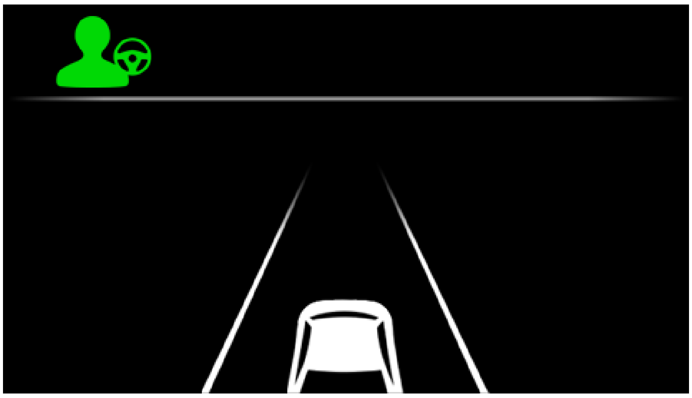

Figure 2.3 HMI for Fully Manual Drive (no automation available). Designed by: CRF (Centro Ricerche Fiat)

Partial automation[1]: Here, both lateral and longitudinal control of the vehicle in the centre lane were managed by the system, with a combination of an Adaptive Cruise Control (ACC) and a Lane-Keeping System (SAE level 2). The system maintained the vehicle position in the centre of the middle lane at 70 mph unless there was a lead vehicle, in which case it would slow down, maintaining a 2 seconds headway. In this condition, the system was

[1] By the time the data for this paper was collected (2017), the definition of SAE level 2 automation was different than what we have today (SAE, 2021). During the writing process, we opted to maintain consistent nomenclature to the one used in the experiment, to match with other publications using the same data (see Madigan et al., 2018).

not able to perform an overtaking manoeuvre. Therefore, drivers were expected to regain control of the vehicle and change lane when they wished to overtake the lead vehicle. In this condition, the system could be disengaged using three different methods: 1) by pulling the right indicator stalk (as with engaging the system); 2) by pressing the accelerator pedal; 3) bymoving the steering wheel more than 2 degrees. In terms of HMI, the system started with the same information as in manual driving and informed drivers when the automation was available, by means of a flashing blue steering wheel icon (see Figure 2.4). Once the automation was engaged by the driver, the colour of the steering wheel icon changed to green. When the automation was disengaged by the driver, the HMI would present a written message stating, "You are back in Manual Mode". The system in this condition also provided a "beep" sound whenever the automation was engaged or disengaged.

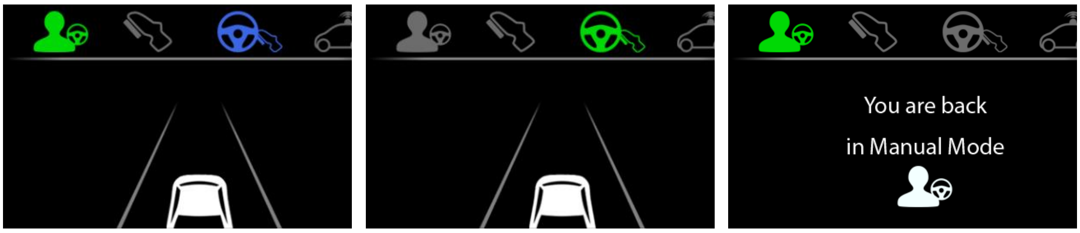

Figure 2.4 HMI for Manual Intervention Required condition. Designed by CRF. Left: automation available, Middle: automation on, Right: driver back in manual control

Full automation: Similar to the previous condition, this system also assumed lateral and longitudinal control of the vehicle. The main difference between this system and Partial automation was that, here, the system could perform the overtaking manoeuvre. The only intervention required from the driver was to move the indicator lever in the direction they wanted the lane change to occur, and the system would then perform the manoeuvre. Regarding the HMI, when the automation was on, a green car icon appeared on the screen (instead of the steering wheel from the Partial automation condition), and the background also turned to green, distinguishing itself from the Partial automation condition. When participants moved the indicator stick, an arrow icon appeared on the screen, pointing to the direction of the manoeuvre.

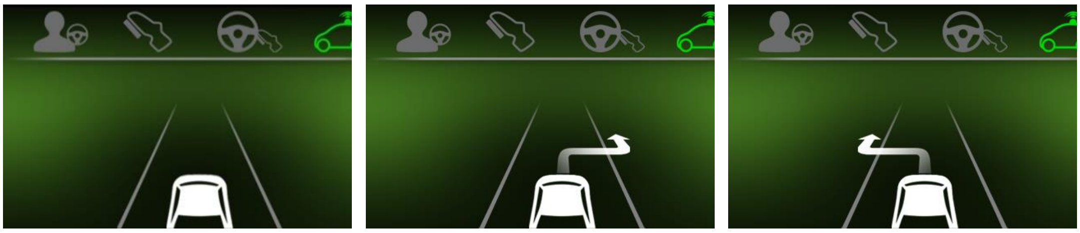

Figure 2.5 HMI (Human-Machine Interface) for Fully Automated Driving condition. Designed by CRF. Left: Automation on, Middle & Right: vehicle changing lane automatically

1.3.4 Statistical analysis

The data was compiled and treated using MatlabR2016a and analysed using IBM SPSS v21. Kolmogorov-Smirnov tests (Conover, 1999) were used to check for normality and showed that part of the data was not normally distributed and presented a slight positive skew. In order to apply parametric statistical tests, logarithmic transformations were made in cases where it was applicable. All the plots presented below are based on the untransformed data, but the ANOVA test results are based on the corrected/transformed samples. An α-value of 0.05 was used as the criterion for statistical significance, and partial eta-squared was computed as an effect size statistic. Where Mauchly's test indicated a violation of sphericity, degrees of freedom were Greenhouse-Geiser corrected.

1.3.5 Research Variables

Eye-tracking measures can be noisy and prone to loss of quality. Therefore, data filtering and selection were applied, using Facelab's algorithms, to avoid biasing the results with low-quality data. The first criterion was gaze quality, which excluded from the dataset all cases with less than 75% good gaze tracking, according to Facelab's algorithm (quality levels < 1). Also, due to some possible detection failures (e.g. when drivers' head was down), some of the data points suggested that drivers looked outside the simulator's projection field. A filtering algorithm was, therefore, applied, excluding all data points that were consistently far away from the interior of the vehicle, or the projection scene inside the simulator dome.

In this study, two main eye-tracking measures were used to assess drivers' visual attention to the road, and vehicle controls, during the 12 lane-change manoeuvres. The first measure involved calculating the percentage of drivers' eye fixations to five main areas, including the road centre (PRC – Percentage Road Centre; Victor, 2005; Carsten et al., 2012; and Louw et al., 2017). As in all previous studies conducted in our laboratory, the reference point for this metric was defined for each participant as the mode of their gaze fixations within a 6° circular limit (Carsten et al., 2012; Louw et al., 2017; Merat et al., 2014; Louw et al., 2017). The other four areas of interest (AoIs) were defined as diagonal sections equally divided from the road centre. The top AoI includes both the far road ahead and the rearview mirror; the left and right AoIs include the view of the side lanes, as well as the wing mirrors and the shoulder checks; and the bottom AoI constitutes both drivers close view of the road ahead and their view of the instrument cluster (where the system's HMI is located). Any variations in this measure over time, and across the three different drives were explored. Fixations were calculated based on a 200 ms threshold.

Drivers' fixations to the AoIs were analysed for each overtaking event, and divided into 17 intervals of 2 s, using the time for exiting the middle lane as a reference starting point. The remaining time windows were decided based on the mean duration of each step of the lane changing manoeuvre performed by the drivers (as can be seen in Figure 2.22). This resulted in 10 intervals before and 7 after the lane change. It must be noted that several different time intervals were tested here (between 1s and 5s), but smaller chunks of time led to fixation percentages of 100% or 0% - suggesting that one second was too short for drivers to deviate their eyes. Larger intervals of 3 or 5 s did not reveal the subtle changes in drivers' gaze behaviour (e.g. from the planning to the execution phase of the manoeuvre, when drivers changed their strategy in a very short period). Therefore, observing changes in 2-second intervals, which started 10 seconds before the mean point at which the lead vehicle began its manoeuvre to the middle lane (flagged by the simulator software) until 10 seconds after the mean point at which the ego vehicle re-entered lane 2 after the overtaking manoeuvre (mean duration of 34.22 seconds) was chosen to assess fixation patterns in this study.

The second metric used was an investigation of drivers' vertical and horizontal gaze dispersion. This was calculated using the mean of the standard deviation of raw gaze yaw and pitch values. A similar approach was used by (Chapman & Underwood, 1998), as an indicator of drivers' scanning behaviour for strategic-based information, due to increasing demands imposed by the driving environment. An increase in dispersion was expected during the planning and execution of the lane-changing manoeuvre in this study, to denote drivers' scanning behaviour during decision-making. We were particularly interested in establishing if this pattern was different across the three drives. It was hypothesised that, at least in manual driving, increasing demands of the drive, such as those required during lane changing, would increase the dispersion of fixations, as drivers moved their visual attention between the lead vehicle, the adjacent lane, the destination lane, and the vehicle HMI, to gather information about their eminent manoeuvre. Understanding whether the same pattern was present for the two levels of automation and similar to that seen in manual driving, was relevant here. Therefore, it was important to establish whether the timing and type of dispersion varied between the three drives, as drivers' responsibility, decision-making, and levels of motor control, changed across the three different drives. However, using overall gaze dispersion based on short time intervals (as the two seconds used in the previously mentioned analysis) could lead to potential data quality issues and, therefore, limitations when interpreting our results. The reason is that gaze dispersion is sensitive to the overall number of observations in the dataset, as it is recalculated at every time interval, ignoring the deviation which happened in the previous iterations. To address this issue, average levels of vertical and horizontal dispersion were plotted for the three drives, based on four main time windows (the size of these time windows was different for each driver, as it was based on the time they spent in each step of the manoeuvres). The four Time Windows were identified as follows: 1) 10 seconds before the lead vehicle entered the middle lane; 2) from the lead vehicle's arrival in the middle lane, until the time when participants started the lane change (M = 9.65 s, SD = 2.91 s); 3) from the point participants exited the middle lane, until they returned to it, thereby completing one lane change manoeuvre (M = 4.57 s, SD = 3.88 s); and 4), 10 seconds after return to lane 2 (see Figure 2.2). The division of those four time windows (TW) is based on Tijerina et al.’s (2005) definition of a lane change task , as the visual attention demands for the task may vary in the different stages of a lane change. TW1 was used to understand how drivers disperse their visual attention during a free drive with no vehicle in front; TW2 is the representation of the decision-making phase of the lane-changing task; TW3 represented the execution phase, and the TW 4 is the point where drivers confirm the appropriate execution of the manoeuvre and return to free driving.

2.4 Results and discussion

1.4.1 Percentage road centre

First, assess whether there were any learning effects in the data sample, a Two-way repeated-measures ANOVA was conducted on the percentage of fixations to the road centre to measure the effect of the order of the overtaking events (13) and DRIVE (Manual drive, Partial automation, Full automation). There was no significant effect of the order of the events [$F(4.566,123.281)=0.965$, $p=.48$, $\eta^2=.034$], or interaction effects [$F(6.273,150.548)=1.526$, $p=.122$, $\eta^2=.06$]. This result suggests that there was no significant learning effect during the whole experiment, indicating that drivers behaved similarly during the whole experiment.

A two-way repeated-measures ANOVA was conducted on the percentage of fixations to the road centre, to measure the effect of Drive (Manual drive, Partial automation, Full automation) and Time Interval (17 intervals of two-second length) (see Figure 6). There was a significant effect of Drive on PRC [$F(1.408,33.796)=5.46$, $p<.05$, $\eta^2=.180$], where Bonferroni post hoc tests (Tabachnick & Findell, 2001) revealed an overall higher percentage of fixations to the road centre during Manual drive (~60%), compared to Full automation (~53%). However, there was no difference between Full automation and Partial automation, or between Partial automation and Manual drive, for this measure.

There was also a main effect of time interval (TI) on PRC scores [$F(5.162,161.846)=8.898$, $p<.001$, $\eta^2=.270$]. As can be seen in Figure 2.6, post hoc tests identified that PRC in the 9th TI was significantly lower than TIs 1-8 and TIs 10-13. This shows how, for all three automation conditions, drivers' visual attention moved away from the road centre immediately (2 seconds) before exiting the middle lane, presumably in preparation for the overtaking manoeuvre. A sharp rise in PRC is then seen during the lane exit phase (TI 11), which was significantly higher than TIs 7-10, 15 and 16. This rise in PRC just before returning the vehicle to the middle lane is expected, showing drivers' attention to the road centre, and particularly the road area relevant for correct repositioning of the vehicle (Tijerina et al., 2005), before automation could be reengaged.

A significant interaction between TI and Drive was also seen [$F(10.859, 260.624)=2.929$, $p <.001$, $\eta^2=.109$], where PRC values for the two automation conditions, Full automation and Partial automation, were generally more aligned, and lower, before the lead vehicle entered the middle lane, i.e. when there was no major interaction required from the driver regarding the lane changing manoeuvre, and the automation was engaged (TIs 1-4). Eye movement patterns then converged for the three driving conditions, when the lead vehicle was in the middle lane, ahead of the ego vehicle, and remained similar until 2 seconds after lane exit (TIs 11-17), where drivers' attention to the road centre then dropped in Full automation, immediately after the manoeuvre execution, since less physical engagement with the vehicle was required.

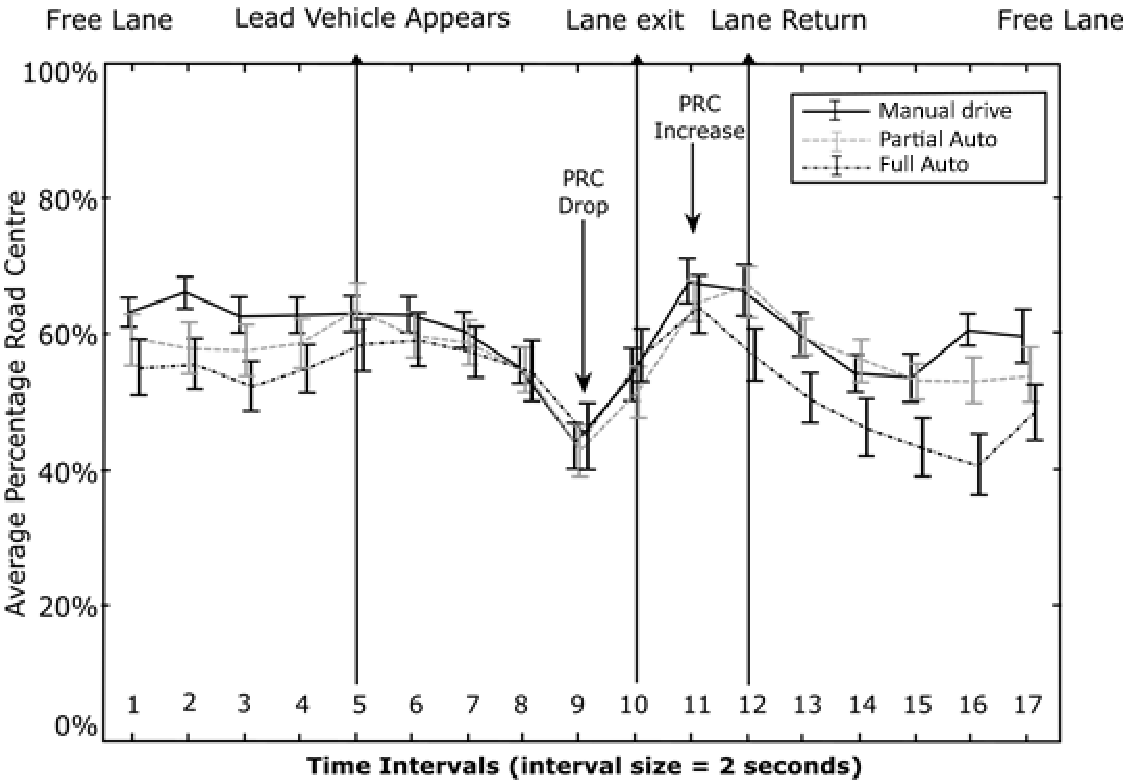

Figure 2.6 Average Percentage Road Centre scores over time during the three drives

The vertical lines represent the starting points for the different phases of the overtaking manoeuvre, which are based on the average duration of each phase for all drivers. The error bars represent the standard error within each distribution.

Taken together, these results suggest some general patterns regarding drivers' information acquisition for these three types of lane-changing task, as governed by the level of automation. For the two automation drives, after attending to the requirement to intervene, drivers exhibit a sudden drop of visual attention towards the road centre, which is similar to that of the manual drive, presumably because they continue to sample information from the road environment, for example looking towards the side mirror and destination lane, to decide whether it is safe to overtake. Further analyses performed indicated that most of the drivers fixated to the right AoI (where the wing mirror is located) before the initiation of the manoeuvre, during TIs 8, 9 and 10, where the drop of PRC was registered. However, this was much higher for the manual drive (Percentage of drivers looking at the right AoI during these time periods pattern: Manual drive = 100%, Partial automation = 89.96%, Full automation = 86.17%). Once they acquired the relevant information, there was a sharp increase in the amount of attention towards the central AoI, for all three drives. An increase in fixations to the road centre is seen for all drives, after lane exit, which shows that, regardless of automation level, all drivers were looking to the destination lane, which they are merging into. This is presumably in order to ensure the path ahead in their destination lane is free, or to coordinate their visual-motor control of the task. Similar results have been reported for lane changing in manual driving by Salvucci & Liu (2002), Salvucci Liu & Boer (2001) and by Tijerina et al. (2005), who showed a reduction in drivers' attention to the side (mirrors and shoulder check) and a focus on the target lane, located in the centre of their field of view. Figure 2.6 also shows that from 2 seconds after they returned to the middle lane, there is a steady reduction in drivers' PRC values, especially for the Full automation condition, with this reduced PRC remaining lower for this drive for 5-8 seconds after lane re-entry (TI 13-17).

Overall, these results illustrate that, even when drivers were not engaged in the physical act of changing lane, their visual attention to the road ahead, and the adjacent lane, was quite similar. These findings are similar to those reported by Mars and Navarro (2012) and suggest that drivers maintain the same level of attention to the driving environment, even when the perceptual-motor connection with the vehicle is broken. Considering that drivers are more likely to gaze towards the most informative information for the given task (Spargue & Ballard, 2004; Sullivan et al., 2012), it seems that the need for decision-making oriented information (such as the ones found in the speedometer and right-side mirrors) overcome the effects of the lack of motor control in lane change tasks. However, it is worth noting that similarities in gaze patterns were only observed during the moments of high decision-making demand, as the drivers' PRC values seem to diverge between the groups the further time away from the actual lane-change task. An analysis of PRC data over the 12 lane-changing manoeuvres showed no significant differences in this pattern over time during TIs 8-10 (which, according to Tijerina et al. (2005) are considered to be the moments of the preparation for a lane-change, [$F(11,44)=.667$, $p > .05$, $\eta^2 = .014$], nor in drivers' fixation percentage to the right AoI [$F(1.690,7.823)=1.665$, $p >.05$, η^2

= .029]. It remains to be seen if longer-term experience with the system affects this pattern.

1.4.2 Horizontal and vertical gaze dispersion

To understand which other areas of the road drivers attend to during lane changes and whether this is different for manual versus automated driving, we analysed the standard deviation of gaze yaw and pitch, plotting the dispersion of gaze for each phase of the lane change manoeuvre. Two repeated-measures, two-way ANOVAs (one for pitch and the other for yaw gaze dispersion) were conducted, to assess the effect of Drive (Manual drive, Partial automation, Full automation) in one of four Time Windows: 1) before the lead vehicle entered the middle lane; 2) time spent behind the lead vehicle; 3) time in offside lane, and 4) time after the overtake manoeuvre was complete (ego-vehicle returns to the middle lane, see Figure 2.2). Regarding horizontal gaze dispersion, the data for drivers' standard deviation of yaw was not normally distributed, showing a slight positive skew, which was corrected through logarithmic transformation.

Analyses of results showed that there was no main effect of Drive [F (2,32) =.845, p >.05, η^2 =.050] on yaw gaze patterns. However, there was a significant main effect of Time Window [F(3,48)=21.803, p <.001, η^2=.577], where horizontal gaze dispersion was significantly higher for TWs 2 and 4 (M = 7.690; 8.348, before and after the manoeuvre, respectively). Based on the results from the previous section (Percentage Road Centre), there was an increased amount of fixations to the side AoIs (left and right, where the wing mirrors are located) during the period of time equivalent to TW 2 (see TIs 8-10, in Figure 2.6). This increased lateral dispersion can be explained by the fact that drivers were inspecting the side lanes in order to decide how to act. These results reaffirm what was found for the PRC analyses, where drivers' visual attention to the road centre varied across time in the same way for the three Drives. These findings reinforce the idea that the nature of the task – in this case, overtaking a lead vehicle – has a strong influence on drivers' horizontal gaze patterns, regardless of the automation condition.

There was also a significant interaction between Time Window and Drive [F(6,96)=2.235, p < .05, η^2=.123], with posthoc Bonferroni tests showing the highest dispersion in yaw gaze for Full automation, during TW 3, i.e. when the vehicle was in the offside lane. As stated above, even if the overall pattern of dispersion was similar since this stage of the lane change was managed by the automated system in Full automation, drivers have no real reason to pay attention to the vehicle's heading, showing more gaze dispersion and less attention to the road centre.

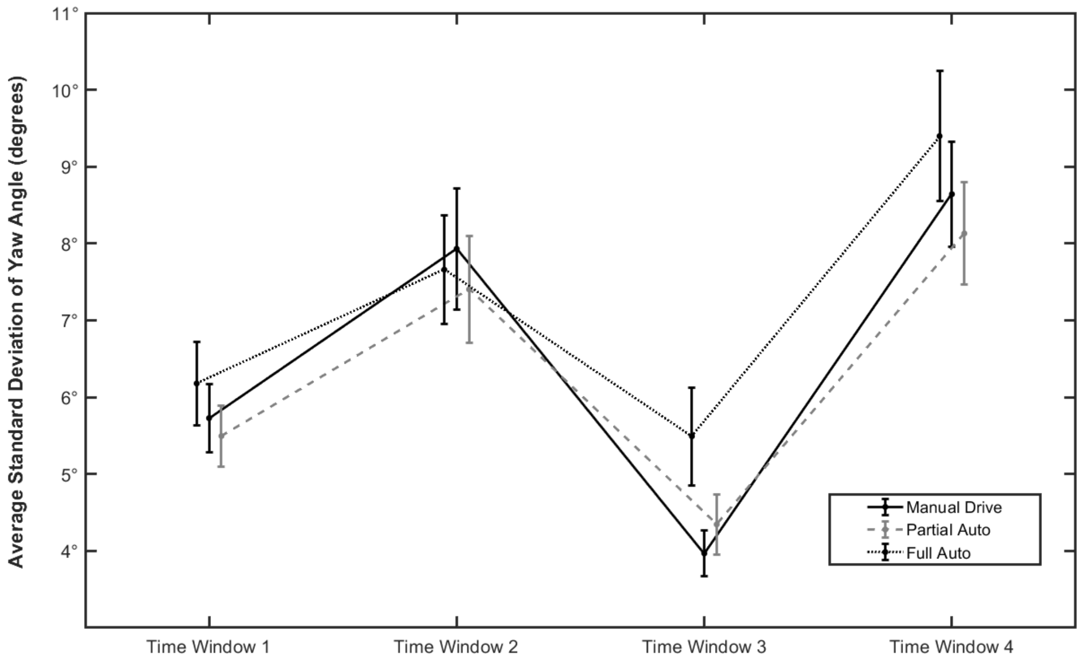

Figure 2.7 Average standard deviation of gaze Yaw over time, during the different automation conditions

TW 1 represents the time 10 seconds before the entrance of the lead vehicle on the middle lane, TW 2 is the time that the ego vehicle spent behind the lead. The error bars represent the standard error within each distribution.

An analysis of drivers' vertical gaze dispersion showed a significant main effect of Drive [$F(2,34)=6.361$, $p<.001$, $\eta^2=.272$], where SD of Pitch was higher overall in Partial automation, compared to Full automation. Results also showed the least degree of variability in gaze pitch for both Full automation and Manual drive. There was a significant effect of Time Window [$F(3,51)=7.606$, $p<.001$, $\eta^2=.309$] on SD of Pitch, which was higher in TWs 2 and 4 (before and after the manoeuvre) than in TW 1 (before lead vehicle entering the middle lane). Finally, there was a significant interaction between Drive and Time Window [$F(3.180, 54.151)=9.973$, $p<.001$, $\eta^2=.370$], where SD of Pitch in Manual drive was higher than Partial automation and Full automation in TW 1, the period before the merging of the lead vehicle into the middle lane.

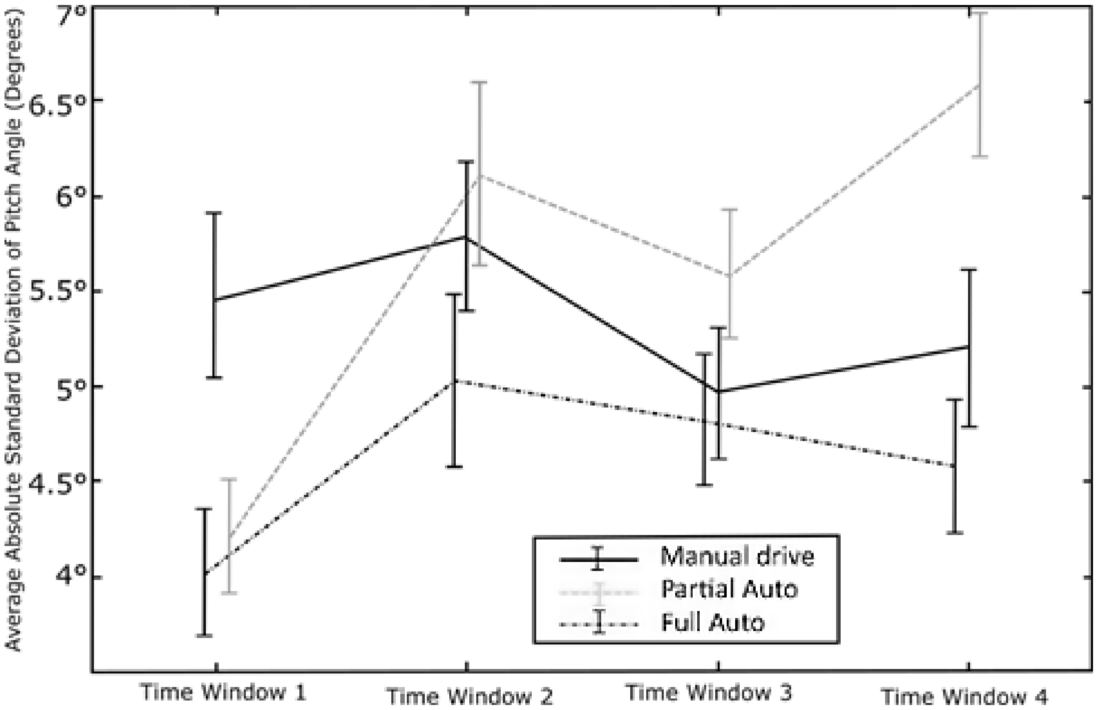

Figure 2.8 Average standard deviation of gaze pitch over time, during the different automation conditions

TW 1 represents the time 10 seconds before the entrance of the lead vehicle on the middle lane, TW 2 is the time that the ego vehicle spent behind the lead. The error bars represent the standard error within each distribution.

A higher SD of Pitch was also observed for Partial automation in TWs 2-4. Further analyses showed that during this time, the place most fixated (after the road centre, which was always the most fixated area) by the drivers in Partial automation condition was the bottom (11% in TW2 and 15.45% in TW4). These results suggest that drivers' need to acquire additional information was highest during the Partial automation condition when their attention to the actions of the lead vehicle and information provided by the HMI (located in the bottom AoI) was highest. As this was the only condition where a transition of control to manual was required, the significant increase of drivers' gaze dispersion towards the bottom AoI during TW1 and TW4 suggests that drivers used the vehicle HMI mostly during Partial automation, to assist with information about the disengagement/re-engagement of the system. On the other hand, the low levels of Pitch SD in Full automation suggest a lesser urgency for drivers to access the information presented in the instrument cluster (both the automation HMI and speedometer), also suggesting that drivers trusted the automated system, perhaps even pressing the 'lane changing button' on the steering wheel, without looking down at the HMI. Following the same logic used in Sullivan et al. 's (2012) study, assuming high uncertainty of specific information (due to the induced

OOTL state), drivers seemed only to see value in the HMI information during moments of transitions of control.

Figure 2.8 shows how drivers' pitch gaze dispersion is affected by the different demands imposed by the driver-vehicle-environment (Crundall et al., 2003), and that this is not the same for the three different drives. In TW1, where there was no vehicle in the middle lane, the only condition which required attention to heading and speed control was Manual drive, which shows the highest vertical gaze dispersion. As outlined above, for TW 2 and 4, drivers in Partial automation had one extra task, when compared to the two other conditions: transition of control from automation to manual mode, and vice versa, which accounts for the higher SD of gaze in this condition, and highlights the need for reliable and timely information for drivers for such transitions of control.

2.5 Conclusion

The goal of this paper was to evaluate the impact of different levels of motor control requirements for task execution on drivers' gaze behaviour during lane changing manoeuvres assisted by vehicle automation. To do so, drivers' percentage of eye fixations to the road centre, as well as gaze dispersion metrics were compared between different test conditions in a lane change task. For each condition, drivers were required to intervene manually with different intensities (control the whole task, transition control to overtake, push the indicator lever to allow automated lane change) in order to complete the manoeuvre.

Percentage road centre (PRC) analyses showed that, during moments of low task demand, drivers' attention to the road centre was lower whenever they were not in active control of the driving task. On the other hand, the differences in their gaze behaviour were quickly resumed (as also reported by Louw et al., 2017) whenever drivers moved closer to the lane change event. Regardless of the level of vehicle automation, drivers' visual attention was directed away from the centre of the road at the same time, immediately before the initiation of an overtaking manoeuvre, which was then refocused towards the road centre during its execution. The observed pattern is similar to that reported in previous literature on manual lane change (Gipps, 1986; Salvucci & Liu, Boer 2001). This result leads us to the assumption that, regardless of drivers' manual engagement with vehicle control, the demands imposed by the task in hand seem to directly affect the way they sample their surroundings for information (Spargue & Ballard, 2004), even if they do not have to actively interact with such information.

In general, drivers' horizontal gaze dispersion was not significantly affected by the different levels of motor control requirements. On the other hand, drivers' vertical gaze dispersion was higher during times when a transition of control was required, with further analysis confirming that this dispersion was generally targeted to the bottom AoI, where the system interface was located. This result suggests that HMI information is especially useful during moments of transitions of control, probably to confirm whether the transition was successful or not, as the interface was the only information source about the system status. Therefore, system designers should consider prioritising a clear identification of system status on vehicle HMI since our results suggest such information encourages drivers to move their eyes towards that area.

This study supports Mackenzie & Harris' (2015) assumption that drivers not in physical control of the driving task change the focus of their visual attention, based on new monitoring priorities. The results observed also suggest that system-based information on an interface is generally not a priority for drivers in automation, outside moments where a transition of control is required, with drivers preferring to direct their attention towards the outside road environment. The implications of these findings are an important consideration for road safety, if drivers become complacent and over trust system information (Miyajima et al., 2015), especially during silent automation failures, where a Take-over-Request by the automation is absent (Louw et al., 2019).

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3. Using Markov Chains to Understand Drivers' Gaze Transitions During Lane-Changes in Manual Vs. Automated Driving

Abstract

This paper reports the results of a driving simulator study, which analyzed differences in drivers' raw gaze transition patterns during different stages of a lane-change maneuver, conducted during manual, partially and conditionally automated driving. To understand whether the different levels of driving affected behaviour, and particularly how visual attention was distributed during a lane-change maneuver, a Markovian chains approach was used to compare gaze transitions between the different information sources available in the surrounding road and cockpit environment, for each of the three drives. The results indicate that during partial automation drivers initiated fewer safety-related inspections – such as to the wing mirrors - throughout the whole maneuver, possibly because they were focusing on managing the transition of control from automation, in order to change lane. Drivers in this condition also had a higher probability of checking the system's HMI, to verify the automation's status. In contrast, during conditional automation, the lack of a need for vehicle control by the driver resulted in more gaze transitions between information sources, and in a much more dispersed pattern, with less focus towards the road center. Finally, drivers generally only deviated their gaze towards information related to aspects of vehicle control they were responsible for, which we conclude could make them susceptible to missing hazards during both routine and safety-critical take-overs.

3.1 Introduction

It is generally agreed that the lack of a need for manual control of the vehicle, as imposed for instance by highly automated vehicles (AVs), removes the driver from the decision-making and control loops (Louw & Merat, 2017), requiring them to scan the environment and acquire appropriate situation awareness (Endsley, 1995) when they are required to reengage with the driving task (Merat, et al., 2018). In complex environments, and when drivers are not continually monitoring the road, but are required to resume manual control, this rebuilding of situation awareness is normally required within a short time window (Louw & Merat, 2017). In addition, acquiring the right information at the right time requires driver attention to various parts of the road environment, and the Human Machine Interface (HMI), which should be providing drivers with the correct information, regarding automation status and, possibly, likely actions from the vehicle. In most circumstances, this information is provided to drivers at the same time, but it is not clear how drivers divide their attention between each of these sources, and how this is affected by the level of automation, or type of maneuver required.

When considering a lane-change maneuver, for example, to overtake a lead vehicle, drivers are required to acquire a large volume of specific information, before deciding how to act (Gipps, 1986). According to Chovan (1994), most of the accidents related to lane-changing scenarios could be avoided if drivers had performed the correct safety inspection procedures. Fitch et al., (2009) complement that argument, when they identified that drivers who do not inspect the rear-view mirrors, and have long glances away from the road center have a higher probability of being involved in a crash during lane-changing tasks. Previous work on manual lane-changing behaviour has outlined the most common visual safety inspection patterns during the different stages that lead to a lane-change maneuver (Tijerina, Garrott, Stoltzfus & Parmer, 2005; Fitch et al., 2009; Salvucci, Liu & Boer, 2001). For example, Tijerina et al. (2005), have shown that prior to the execution of the maneuver, drivers generally shift their eyesight to the wing mirrors, but always shift visual attention back to the center of the road, immediately after this. When the driver initiates the maneuver, Salvucci, Liu & Boer (2001) have shown that drivers’ gaze transitions generally shift between the obstacle to be overtaken, and the destination lane. However, currently, there is a limited understanding of the drivers’ distribution of eye movements during lane-changes for different levels of automated driving.

This paper provides further analysis of data from a previous study which considered drivers' gaze behaviour during automated lane-change maneuvers (Gonçalves, Louw, Madigan, Quaresma & Merat, 2020), conducted as part of the EU-funded AdaptIVe project. Here, we found that the drivers engaged with different levels of vehicle automation deviate their eyesight away from the road center at similar times, as measured by Percent Road Center (PRC, see Victor et al., 2005). However, the location of drivers' visual attention was found to vary, based on the level of automation. Gaze was more spread vertically for situations where a transition of control was required (during partial automation), showing that drivers looked to the HMI placed on the dashboard. However, gaze patterns were more horizontally spread when there was no need for resumption of manual control, during conditional automation, where drivers seemed to check the maneuver execution managed by the automated lane-change. To our knowledge, this, and other research in the lane-change context (e.g. Miyajima at al., 2015), have only analyzed mean gaze fixations to different areas of interest, and drivers' average horizontal and vertical gaze dispersion. However, we argue that there is value in understanding how, and when, drivers shift their attention across the different information sources, to understand what information is used during the decision-making process required for a lane-change maneuver (Mourant & Rockwell, 1971; Underwood, Chapman, Brockelhurst, Underwood & Crundall 2003).

Therefore, utilizing a Markovian chains approach (Mukherjea, 1983) this study investigated how drivers distribute their attention across different parts of the road environment and vehicle, during a lane-change maneuver, and whether this behavior is different for partial, versus conditional, automation. This technique has been used in the past to study drivers' gaze behaviour in different situations, to understand drivers' intentions during a lane-change, and model their scanning strategies (Underwood et al., 2003; Salvucci, Mandalia, Kuge & Yamamura, 2007). It can be argued that, as vehicles become more automated, this knowledge will help design more informative in-vehicle interfaces. Based on the objectives purposed above, the following research question was addressed: what are the differences in drivers' visual scanning strategies during the stages that constitute a lane change maneuver during different levels of vehicle automation, and how is this different to when in manual control?

3.2 Methods

Twenty-nine fully-licensed UK drivers (15 male) participated in this study. All participants had at least two years' driving experience ($M = 13.62$, $SD = 9.62$) and were aged between 21 and 60 years ($M = 34.21$, $SD = 8.94$). All participants were recruited through the UoLDS participant database, and received £20 for partaking. The experiment was conducted in the University of Leeds Driving Simulator (UoLDS), which is a high-fidelity, motion-based driving simulator, with a 300o projection dome, containing a fully equipped Jaguar S-Type cabin is installed, with fully operational controls. Participants' eye movements were recorded using a v4.5 Seeing Machines FaceLab eye-tracker, recording at 60Hz.

A within-participant, 3 (Drive: manual, partial automation[2], conditional automation) x12 (lane-change maneuver number) repeated-measures design was used, with all participants completing the three drives (presented in a counter-balanced order). Following a short practice drive, participants completed three experimental drives. For the two automation drives, participants were instructed to maintain a speed of 70 mph (national speed limit) and to stay in the center of the middle lane, whenever possible. In each of the three drives, participants experienced a total of 12 overtaking events (Figure 3.1). The overtaking events were initiated by a slower vehicle (50 mph) entering the middle lane from the left lane (grey vehicle inFigure 3.1), blocking the path of the ego-vehicle. Participants were instructed to overtake these vehicles and to return to the middle lane once they had passed this vehicle. This scenario was previously used in other studies from the same research group (Madigan et al., 2018, Goncalves et al., 2020). The overtaking task was chosen for assessing drivers' lane-change behavior, to be consistent with previous studies on the same topic (Tijerina et al., 2005).

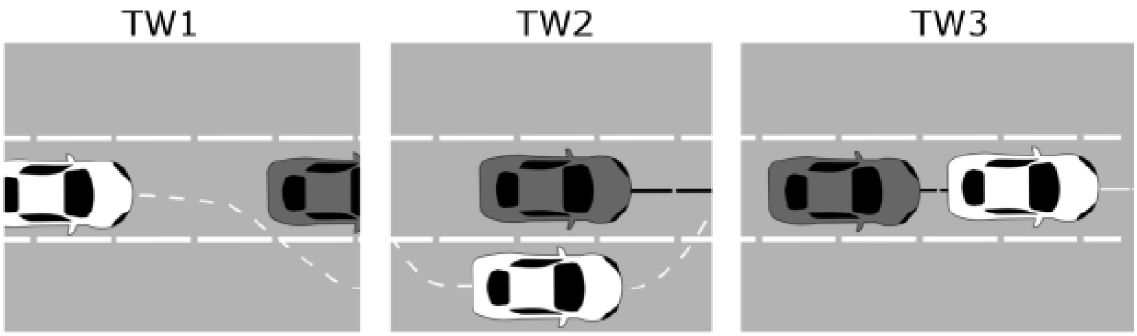

Figure 3.1 Representation of the scenario, showing the over-taking maneuver (TW= Time Window)

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[2] By the time the data for this paper was collected (2017), the definition of SAE level 2 automation was different than what we have today (SAE, 2021). During the writing process, we opted to maintain consistent nomenclature to the one used in the experiment, to match with other publications using the same data (see Madigan et al., 2018).

In the manual drive condition (MAN), drivers were in full control of the vehicle at all times. In the Partially Automated Drive (PAD), when engaged, the automated driving system maintained lateral and longitudinal vehicle control. However, to perform the lane-change maneuver, drivers were required to disengage the automation and perform the lane-change, by pressing a disengagement button or moving the steering wheel. They were then required to return to the middle lane and re-engage the automation as soon as it was available. The HMI displayed the system's status and was placed on the dashboard. In the Conditionally Automated Drive (CAD), the automation was capable of both lateral and longitudinal control of the vehicle, and performed the lane-change maneuvers, with no need for the driver to resume manual control. However, to initiate the lane-change maneuver, drivers had to move the indicator lever. The HMI showed the system status, and an indication that a lane-change was being performed by the system. The definitions of the levels of automation used here are the same to the ones adopted in our previous studies (Madigan et al., 2018; Gonçalves et al., 2021).

For the analysis, the overtaking maneuver was split into three time windows (TW; see Figure 3.1), guided by the work conducted by Tijerina et al. (2015) and Gipps (1986). TW1 began from when the lead vehicle entered the middle lane, until the ego-vehicle exited the middle lane. In this study, we define that a vehicle enters a lane when both of its front wheels cross the division between lanes. TW2 began when the ego-vehicle exited the middle lane, until the point it returned to the middle lane. TW3 began when the ego vehicle returned to the middle lane until 10 s after this maneuver. The dependent variable used for the analysis of this study was the transitions of drivers' gaze points across five AoIs (Areas of Interest). The AoIs used here were based on Carsten et al. (2012, see Figure 3.2), which were anchored around the center of the road (6 degree circular area centered around the mode of gaze fixations during manual driving). The other four AoIs were equally divided horizontally and vertically. These comprised of the right (the right wing-mirror); top (or rear-view mirror); left (shoulder check or left-wing mirror), and bottom (instrument cluster and system's HMI). A gaze transition was defined as the movement of drivers' eye gaze (X, Y position) from one AoI to another. Gaze-based transitions were used instead of fixation-based transitions, because short glances to the mirrors, for example, are often not detected by fixations. For the data analysis, this study opted to follow a similar approach to Underwood et al. (2003), as it allowed a direct comparison between test conditions. In this case, we used the data from the baseline (MAN) drive as the ground truth, and investigated how gaze transitions for the other two conditions (PAD & CAD) differed from it.

The Markovian chains method (Mukherjea, 1983) treats data from the gaze transitions in each driving condition, and TW, using a binomial model, in a way that every gaze transition from A to B had one chance N to happen, and estimated based on the observed sample. N was calculated by the division of the number of gaze transitions from A to B, by the total number of transitions that started in A. The N values were used as a parameter for statistical tests to identify where/ if specific gaze transition (A, B) could be considered more or less probable to happen in each automation condition and TW, when compared to the manual drive. As the data was not normally distributed, Wilcoxon’s tests were applied to measure the differences in the paired-samples of possible transitions. This paper will only report the ones with significant differences.

3.3 Results and discussion

Figure 3.2 and Table 3-1 show the results of the Wilcoxon tests, which are divided by levels of automation and TWs. Black arrows indicate that there were significantly more transitions from one AoI to another, compared to what was observed during MAN, while gray dashed arrows indicate that, in both PAD or CAD, there were significantly fewer transitions compared to MAN.

Figure 3.2 shows that PAD had a significantly higher gaze transition activity from bottom to left, and from left to bottom during TW1. A higher frequency of drivers' glances towards the bottom was also observed from the center and from the left during TW3. This pattern is in line with the change in drivers’ role during the transition of control from automation to manual (TW1) and vice versa (TW3). For example, this higher frequency of gaze towards the bottom can be explained by drivers’ need to look at the HMI, in order to check the system status information (as suggested by Louw et al., 2017a, b). These results, therefore, support the hypothesis presented in Gonçalves et al. (2020), which advocates in favor of the importance of system status information on the HMI during transitions of control.

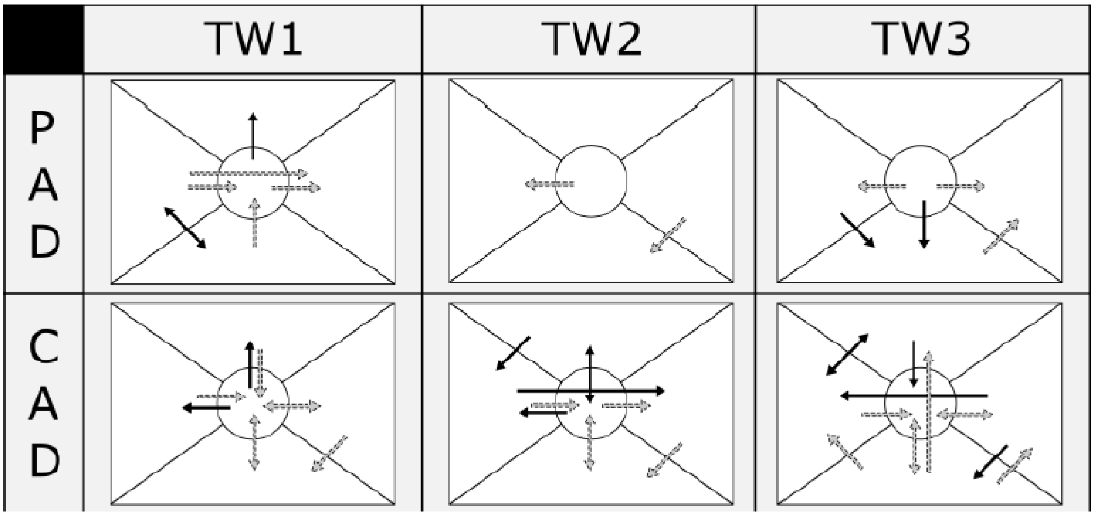

Figure 3.2 Representation of the differences in gaze transition frequency between AoIs for PAD and CAD compared to MAN (dotted= sig. lower than MAN; solid= sig. higher than MAN)

Table 3-1 Results of the Wilcoxon's tests on the frequency of gaze transitions between Areas of Interest

TW 1				
Drive	Starting AoI	Ending AoI	Z	P
PAD	Center	Top	-6.189	<.001
	Center	Right	-4.037	<.001
	Left	Center	-12.199	.028
	Left	Bottom	-3.003	.003
	Left	Right	-2.376	.017
	Bottom	Center	-2.173	.03
	Bottom	Left	-2.912	.005
CAD	Center	Top	-3.215	<.001
	Center	Left	-4.534	<.001
	Center	Bottom	-7.943	<.001
	Center	Right	-3.401	<.001
	Top	Center	-2.988	.003
	Left	Center	-4.2	<.001
	Bottom	Center	-5.037	<.001
	Right	Center	-2.536	.011
	Right	Bottom	-3.819	<.001

TW 2				
	Starting AoI	Ending AoI	Z	P
PAD	Center	Left	-2.119	.034
	Right	Bottom	-2.121	.033
CAD	Center	Top	-3.127	.002
	Center	Left	-3.464	<.001
	Center	Bottom	-6.638	<.001
	Center	Right	-3.338	<.001
	Top	Center	-3.495	<.001
	Top	Left	-2.708	.007
	Top	Center	-3.383	<.001
	Left	Right	-1.983	.047
	Bottom	Center	-3.401	<.001
	Right	Bottom	-2.347	.019

TW 3				
	Starting AoI	Ending AoI	Z	P
PAD	Center	Left	-4.182	<.001
	Center	Bottom	-4.403	<.001
	Center	Right	-2.572	<.001
	Left	Bottom	-1.42	.016
	Bottom	Right	-3.176	<.001
CAD	Center	Right	-2.198	.028
	Top	Center	-4.818	<.001
	Top	Left	-2.19	.038
	Left	Center	-6.532	<.001
	Left	Top	-2.229	.026
	Bottom	Center	-4.696	<.001
	Bottom	Top	-2	.045
	Bottom	Left	-3.536	<.001
	Bottom	Right	-2.025	.043
	Right	Center	-2.73	.006
	Right	Left	-2.304	.021
	Right	Bottom	-3.003	.003

During TW1, drivers in PAD had a significantly lower frequency of moving their eyes towards the road center (from the bottom and left) when compared to the manual drive. A lower frequency of gaze transitions towards the right from the center and left were also observed here, which suggests that drivers performed fewer glances to the mirrors to see the vehicle on the offside lane (left) and to the road center, to check the distance from the leading obstacle. During TW 2, there was a lower frequency of gaze transitions from the center to the left and from the right to the bottom. Overall, in this time window, drivers' visual attention was less dispersed than during the manual drive, probably because they were checking their speedometer (bottom) and the lead vehicle (left) less often. Finally, in TW 3, drivers in the PAD condition performed fewer mirror/shoulder checks coming from the center and bottom than the ones in MAN. According to the literature, (Tijerina et al., 2005; Salvucci, Liu & Boer, 2001; Fitch et al., 2009), these are common safety-related glance checks during the lane-change maneuver. This drop in such glances may be because of the increased workload of the driver, imposed by the transition of control, which is in line with studies reported by Crundall & Underwood (1998) and Louw et al. (2020), who suggest that drivers have reduced scanning capabilities under high workload conditions.

It is evident that drivers presented a more scattered distribution of gaze transitions during CAD compared to MAN. During TW1, a lower frequency of gaze transitions towards the center were observed, when compared to the manual drive. The same reduction of gaze towards the center was identified in TW2 (from left and bottom) and TW3 (from left, bottom and right). Analysis of this conditions also showed a higher frequency of gaze transitions not passing through the road center during TW2 (from top to left, and from left to right) and TW3 (from top to left, from left to top, from right to left, from right to bottom). It appears that the lack of a need for vehicle control during the task reduces the probability for drivers to gaze back to the road center, after attending to other AoIs. These results are in line with others who have shown that during automation drivers have a more dispersed gaze, as the manual control of the vehicle is not required (Miyajima et al., 2015; Louw & Merat, 2017).

Since drivers in CAD were not required to monitor the vehicle's speed, the gap for a lanechange, system status, or the vehicle's position during TW1, a lower frequency of gaze transitions towards the right from the center and towards the bottom (from the center and from the right) were observed. Since drivers still didn't need to monitor their speed in TW2, results showed a lower frequency of gaze to the speedometer (bottom) from the center, and from the right in this TW. Fewer glances towards the destination lane from the center were also observed here. As the drivers were not responsible for controlling most of the activities related to the task, it is believed that they had no real motivation to look for information as much as they would in a manual drive. The results above support our previous assumption that drivers tend not to monitor what they are not directly in control of (Gonçalves et al., 2020; Louw & Merat, 2017).

3.4 Conclusion

The aim of this study was to understand how drivers disperse their visual attention, during manual and automated overtaking events by using a Markovian Chains approach. Our results indicate that during partial automation, whenever a transition of control was required, drivers had a lower probability of performing safety-related glances, such as shifting their gaze between the side mirrors and the road center, possibly because they needed to verify the status of the system on the HMI. It has been argued that the reduction of such safety-related glances may reduce hazard detection ability (Fitch et al., 2009; Chovan, 1994), therefore increasing the likelihood of crashes.

The results of this study also support our previous findings (Gonçalves et al., 2020), that by removing physical control and decision-making responsibility from drivers, automation reduces their propensity to scan the environment and look for information that might be relevant for task execution. Therefore, removal of manual vehicle control may cause drivers to be more reliant on good system performance and suitable HMI, which, if absent, makes them less capable to respond to automation failures (Prasuraman & Riley, 1997; Miyajima et al., 2015). This induced reliance on timely and suitable information ultimately reinforces the fact that badly designed automated systems and related interfaces may bring with them additional and unforeseen risks to the road environment, reinforcing the ironies of automation (Bainbridge, 1981). As automation reduces drivers' motivation to scan the road and vehicle environment, this study highlights the need for future studies which identify how drivers' attention can be guided to the correct location and information, at different stages of the transition process.

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4. The Effect of Driver Engagement and Presence of Obstacles on Drivers' Gaze Behaviour Patterns During Non-Critical Transitions of Control From Vehicle Automation

Abstract

This driving simulator study aimed to evaluate the effect of drivers' level of engagement with the driving task and the presence of a lead vehicle on their gaze behaviour during non-critical transitions of control from automation. Drivers' attention during Level 3 automation was controlled via engagement in a visual-manual non-driving related task (NDRT). Results showed a significant impact on drivers' visual attention, with those engaged in the NDRT having a more dispersed gaze pattern. Overall, the presence of a lead vehicle did not influence drivers' gaze behaviour during the transition. However, drivers engaged in the NDRT were more sensitive to the presence of the lead vehicle as they resumed control, using the information on the instrument cluster to establish their speed and headway. This study shows the implications of engagement in NDRTs and highlights the importance of providing the correct automation-based information to drivers, as they resume control from automation.

4.1 Introduction

In the field of Human Factors for autonomous vehicles, a large body of literature states that vehicle automation interrupts drivers' visuomotor coordination with the driving task (Mole et al., 2019) and removes them from both the decision-making and control loops (Merat et al., 2019). Empirical studies suggest that this has a detrimental impact on drivers' abilities to safely resume control of the driving task (e.g. Louw & Merat, 2017; Dambock et al., 2013; Blommer et al., 2017), for conditional automation (Level 3, SAE, 2018), where the driver is allowed to have their visual attention entirely away from the driving task (engaging in non-driving related tasks – NDRTs) but is still required to be ready to resume control, whenever a system limitation is reached.

In order to safely resume control from vehicle automation, drivers first need to acquire sufficient levels of situation awareness (see Endsley, 1995 for a complete definition of the term), which has been presumably lost, as they relinquished control from the driving task. To achieve this goal, the drivers must follow a visual scanning procedure, and quickly sample information from both the road environment and automation in a process called described as "situation awareness recovery" (SAR, Gartenberg, 2014). This process is based on the Memory for Goals model (Altman & Trafton, 2002), which correlates situation awareness with the drivers' current stored information in their short-term memory, regarding the situation in hand. In this model, the pattern and allocation of drivers' visual attention (in terms of eye movements) follows a goal-based, top-down structure (see Carrasco, 2011 for a detailed definition of the term). In other words, after identifying the goals for the task in hand, drivers will shift their gaze towards the location where they believe they will find the information they are missing in their internal representation of the situation. This direction of gaze is determined by the driver's personal experience, and their remaining stored memory about the event, which includes their moment-to-moment control of the driving task, before the activation of automation.

Even though SAR is considered to follow a top-down structure, a systematic literature review by Borji & Itti (2013) suggests that any gaze behaviour model is also prone to noise from a bottom-up structure (attention saliency). In the context of a transition of control from vehicle automation, this can include any potential environmental, or vehicle-based, element that is contextually relevant (e.g., an approaching lead vehicle, imposing a potential collision, or an auditory/visual collision warning). Many studies have reported that drivers' gaze behaviour during transitions of control is linked to the level of automation (Carsten et al., 2012), which can have safety-critical implications. For example, Zeeb et al. (2015) reported that drivers who made longer glances away from the road centre on approach to a safety-critical transition, had longer takeover times, resulting in increased crash propensity. Similarly, Louw & Merat (2017), Louw et al. (2016) and Louw et al. (2018) found that the more drivers were taken "out of the loop", by reducing the amount of visual information available to them in a simulated driving scene, the more dispersed their eye gaze during automation and the transition of control process. However, these differences in gaze behaviour were found to be quickly resolved within two seconds of a takeover request, with most drivers focusing on the road ahead, when the visual scene re-appeared. Here, the visual looming cue of an expanding lead vehicle was found to be a good predictor of drivers' takeover time. These results suggest, therefore, that, eye gaze is a useful measure for understanding how bottom-up stimuli can influence top-down processing during for safety-critical transitions of control in automation.

However, to date, few studies have considered how gaze is dispersed in more non-critical takeover scenarios, for example, in the absence of a lead vehicle, and what information from the environment and vehicle are used by drivers in these conditions. Using Percent Road Centre (Victor, 2005) as a metric for gaze dispersion/concentration results from manual driving suggest that drivers predominately look at the road centre area, when not engaged in visual NDRTs with gaze also interspersing between a lead vehicle and the road ahead, during car-following tasks (Kountouriotis & Merat, 2016). Studies also suggest "look ahead fixations" in driving guide our locomotion in the environment during manual control. However, as the link between vehicle steering control and eye gaze is broken by automation (Mole et al., 2019), it is important to understand where drivers look before resuming control of the vehicle, and how this is influenced by top-down versus bottom-up information processing, including how drivers' attention is divided between salient stimuli, such as lead vehicles and in-vehicle HMI. Based on the arguments presented above, we defined the following research questions:

1. How does the transfer of control from Level 2 and L3 automation affect drivers' visual attention before a non-safety-critical event?
2. Do drivers' gaze patterns change, based on the presence of a lead vehicle during the transition of control?

To answer those research questions, we conducted a car-following study as part of the L3Pilot consortium, in partnership with Toyota Motors Europe. In this experiment, drivers were assigned to one of two groups: Level 2 and Level 3 and performed several transitions of control. In line with the SAE guidelines (SAE, 2018), drivers in Level 2 were asked to monitor the road at all times (hands off wheel), whereas those in Level 3 were asked to engage in a secondary non-driving related task (NDRT) while the automation was on. Half of the transitions were performed with a lead vehicle, while the other half were performed on a free lane.

4.2 Material and methods

4.2.1 Participants

Thirty-two participants were recruited via our driving simulator database. The recruitment process followed approval from the University of Leeds Research Ethics Committee (Reference Number: LTTRAN - 054). Due to poor gaze capture, data from four participants had to be removed from the analysis, resulting in a total sample size of 28 participants (9 female, 19 male). All participants were UK licensed drivers with normal or corrected-to-normal vision. Their average age was 38 (SD = 14.34), while their average annual mileage was 10,209 KM (SD = 7,775), and no previous experience with the driving simulator or any kind of L2/3 automation. The experiment lasted about 2 hours, and participants received £25 for taking part in the study.

4.2.2 Materials

The experiment was conducted in the University of Leeds Driving Simulator (UoLDS): a 6-degrees of freedom, high fidelity driving simulator. The simulator includes a 4m-projection dome with a 300° projection angle. Inside the dome, a fully functional Jaguar S-Type vehicle cabin, with original controls, is installed. Drivers' gaze was captured by a Seeing Machines Face Lab model eye tracking device, capturing data at 60 Hz. A 400X600px VGA touchscreen Lilliput display was installed near the gear shift, for displaying the NDRT.

4.2.3 Driving scenario

The experiment scenario was composed of an urban car-following task, where drivers needed to drive at around 40 mph, along a 2-way urban road, and follow a lead vehicle (driving at a constant speed of 38mph). When the lead vehicle was presented, automated car-following was achieved at two different time headways (0.5 or 1.5s). Participants used a dash-based HMI to know when automation was available. Figure 4.1 shows the representation of the urban environment used in the experiment scenario, as well as the information present on the vehicle's instrument cluster.

Figure 4.1 Example of the experimental scenario and instrument cluster with the automation status symbol (Left: automation not engaged, Right: automation engaged) and the vehicle speed (mph)

During automated car-following, there were four events when the automated system reached the end of its operational design domain, due to missing lane markings, making the system unbale to keep the vehicle's lateral control, triggering an auditory takeover request (TOR). The takeover request was composed by an auditory warning, requesting the drivers to takeover, followed by a series of continuous "beeps", every second until the automation was disengaged. Here, drivers had 10 s to resume control of the driving task, and continue a manual car-following task, until the automated system was available. A failure to take over control of the vehicle did not result in a crash. In case the drivers were unable to disengage the automation within the given time budget, the system would perform a minimum risk manoeuvre, decelerating the vehicle and disengaging the automation.

4.2.4 Experimental design

The experiment followed a 2x2x2 mixed design, with the level of automation (L2, L3) and time headway (05, 1.5s) as a between-participant factor, and takeover type (with lead, without lead) as a within-participant factor. All factors were presented in a fully counterbalanced order. Since level 3 automation (SAE, 2018) allows the driver to divert their attention away from the driving task and not monitor the system behaviour, participants in Level 3 automation were asked to engage in the Arrows task (Jamson & Merat, 2005; Louw et al., 2020) during the automated drives, simulating potential distractions with NDRTs. On the other hand, drivers in L2 were instructed to monitor the road whenever the automation was engaged. The arrows task is a visual search task where drivers needed to continuously locate and click in one arrow pointing upwards, among a set of arrows pointing to different directions. The task was displayed in a LED touchscreen display, located near the gear shifter (impeding the drivers to sample information from the outside environment), and drivers were instructed to play it whenever the automation as engaged.

For the time headway conditions, half of the experimental runs were done with the vehicle automation following the vehicle in a distance of 0.5s time headway (THW), and the other half with 1.5s THW. For the purposes of this paper, the data for both time headway conditions were amalgamated, since it did have any significant effect on drivers' gaze behaviour. The takeover type varied, based on the presence of a lead vehicle during the takeover events. Here, for two of the four takeovers, the lead vehicle entered a side road, at an intersection, moments before the TOR was issued. The other half of the takeover events did not include a lead vehicle. For those cases, right after the transition, another lead vehicle joined the lane from another intersection 20 m away from the fading lane markings.

4.2.5 Data analysis process

Eye-tracking treatment

As eye-tracking data can be noisy and prone to errors, due to bad quality gaze capture, a series of filter and treatment procedures were performed before the data analysis. First, we defined a minimum gaze capture quality standard for our sample, based on the gaze confidence metric on the eye-tracking software algorithm. All samples selected for this study had to have at least 75% of their overall data points (at a frequency of 60hz), scoring a confidence of 0.8 or higher. For the L3 samples, as their gaze was not trackable while the drivers were engaging with the NDRT, head position metrics were used to estimate gaze location whnever the participants’ eyes were not visible for the eye-tracking device. Fixations were defined as drivers' gaze remaining within a 1° circular area for at least 150 ms. These threshold parameters are consistent with previous literature on algorithms for dispersion-based fixation detection (see Salvucci & Goldberg, 2000; Nyström & Holmqvist, 2010).

The distribution of drivers' visual attention was assessed by calculating the intersection of gaze coordinates with five different areas of interest (AoIs) within the vehicle cab, and driving environment, and two non-AoI categories. These included, 1) Road centre, defined as a rectangular area, covering both lane markings and the location of any lead vehicle during car-following; 2) On road, defined as the windshield area not including the road centre AoI; 3) Instrument cluster, defined as the area containing both the cluster of information on the vehicle's centre stack (HMI) and the top half of the vehicle's steering wheel; 4) Rear and side mirrors, the combination of areas for both side mirrors, and the rear-view mirror; 5) Vehicle cabin, defined as the area containing all gaze inside the vehicle's cabin, not covered by the instrument cluster or rear/side mirrors; 6) Eyes closed; and 7) Other/Eyes not tracked, used whenever the eye-tracking system lost drivers' gaze tracking, and used head estimation to define the gaze location - in the L3 condition, we took this area to include the Arrows task).

The data was processed in MATLAB (version R2016a (Mathworks, 2017)) and analysed using SPSS v21 (IBM Corp., 2012)). A Kolmogorov-Smirnov test was used to check for normality. Where required, positive-skewed data was transformed using logarithmic transformations. Otherwise, non-parametric tests were applied. All figures were generated with the original untransformed data, and the statistics were based on transformed data (if applicable). An α-value of 0.05 was used as the criterion for statistical significance, and partial eta-squared was computed as an effect size statistic. Bonferroni α corrections were applied for the p values in the time time series analysis, to mitigate potential type 1 errors caused by multiple comparisons within the data.

Research variables

We divided the analysis of drivers' gaze for this study into two stages: 1) a time series analysis on drivers' raw gaze distribution across AoIs, and 2) a condensed time window analysis, on drivers' gaze fixation data, through the whole duration of the transition of control process.

For the time series analysis, as takeover times varied across drivers and events, using relative values for the gaze behaviour during the transition of control process would over/underestimate its values, because the transition process varied across participants. To account for this issue, we focused the analysis on a fixed range of time, using the moment of the transition as the reference time point across all drivers. The range selected was 10 seconds before, and 10 s after the transition itself, as the maximum takeover time was 10s. For exploration purposes, the first metric observed was the frame-by-frame distribution of drivers' gaze location to the different AoIs, over time, expressed as a percentage. To understand how drivers dispersed their attention away from the road centre during the time course of the transition, this 20 s time window was divided into 60 intervals of 0.33 s (20 frames). Afterwards, the differences in the proportion of drivers' raw gaze falling on the road centre AoI during each minor interval was calculated using individually paired t-tests. Considering the size of the intervals used for the time series analysis, different time window sizes were tested and the 0.33s was selected since it yielded the most reliable results. The choice for such short intervals was made to align with the research objectives, since longer intervals would not be able to pick up sudden changes on drivers’ attention, and shorter intervals would potentially rise the type 1 error rate, due to the number of repetitive statistical tests performed.

For the condensed time window analysis, all the metrics used were calculated based on the beginning of the TOR (when the auditory message was presented) until the drivers disengaged automation and resumed manual control of the vehicle. The primary metrics used for this data analysis were drivers' average time taken to make a first fixation on the road centre area, and the instrument cluster (in seconds), respectively, and the proportion/probability of drivers' fixation transitions between the defined AoIs. These variables were selected to show potential differences in drivers' initial attentional focus during the transition process, and how this focus is distributed to acquire additional information from the different sources.

The fixation transition probability analysis was conducted using a Markov chain structure [24], which treated the probability for each gaze transition between two AoIs (a,b) to happen as a multi-dependent binomial distribution. In this structure, the only predictor for a given transition towards the location b to happen is the origin of the gaze transition (a). This process generated a table with different values of p (a|b) for each participant, and the effects of the experimental conditions on those probabilities were compared using Kruskal-Wallis tests.

4.3 Results

4.3.1 Raw gaze distribution

Figure 4.2 shows the allocation of drivers' eye gaze to the different AoIs, during the transition of control. Results show a clear difference between the two groups, with drivers in the L3 group focusing on the Arrows task, which explains the large degree of "eyes not tracked" in the Figure, but also illustrates how visual attention shifts slowly to the road centre and centre console as a TOR request is provided. For the L2 group, in the moments before the transition of control, drivers' gaze was primarily concentrated around the road centre area (dark blue), with a secondary focus on the instrument cluster area (orange). This Figure illustrates the areas containing the most valuable information for drivers during a transition of control, as they include the road environment, the vehicle's speed, and the automation system's status. Morando et al. (2020) also observed a similar pattern in an on-road study of drivers using L2 (SAE, 2018) Tesla vehicles.

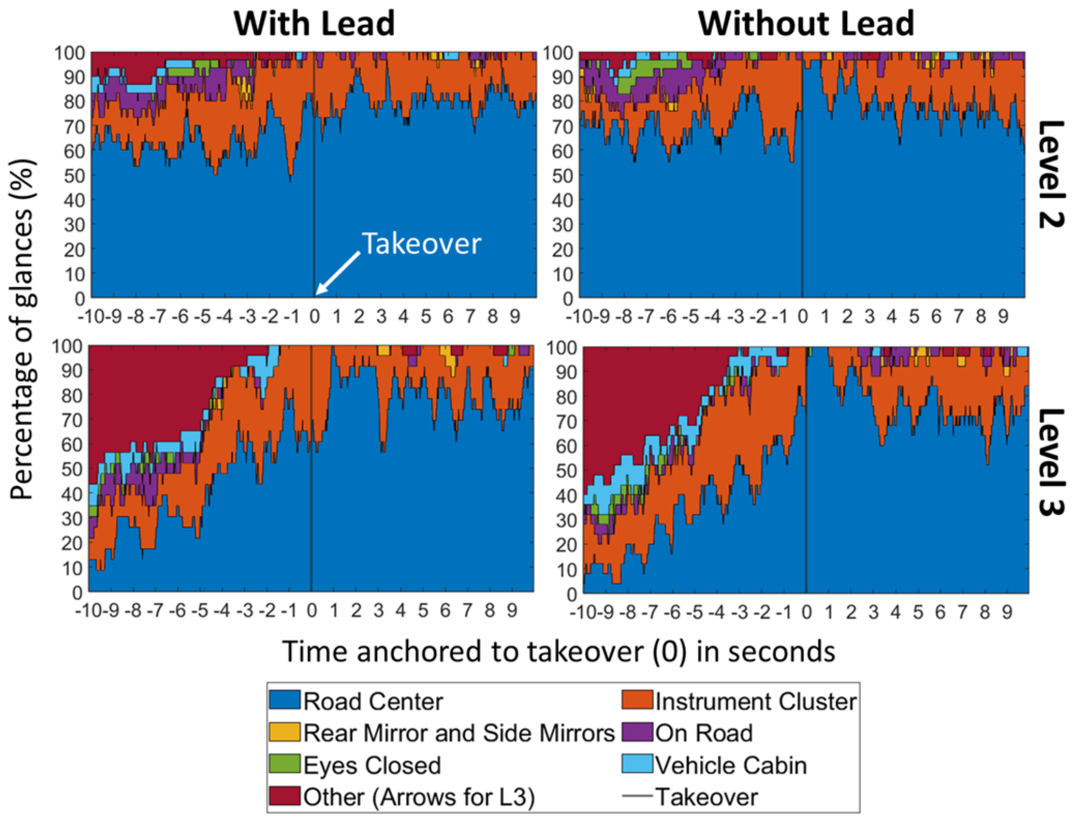

Figure 4.2 Graphical representation of the drivers' distribution between the AoIs in the 10 s before, and 10 s after the transition of control

The black line in the centre represents the takeover time (ToT), which was the anchor point for the data selection.

To explore potential differences in how drivers attend to the potential hazards on the road, and the other information present on the environment, several t-tests were performed, to investigate the effects of the experimental conditions on drivers' concentration of gaze to the road centre, over time. As mentioned in the methodology section, the p values for the t-tests were Bonferroni corrected, to account for the multiple comparison error propagation.

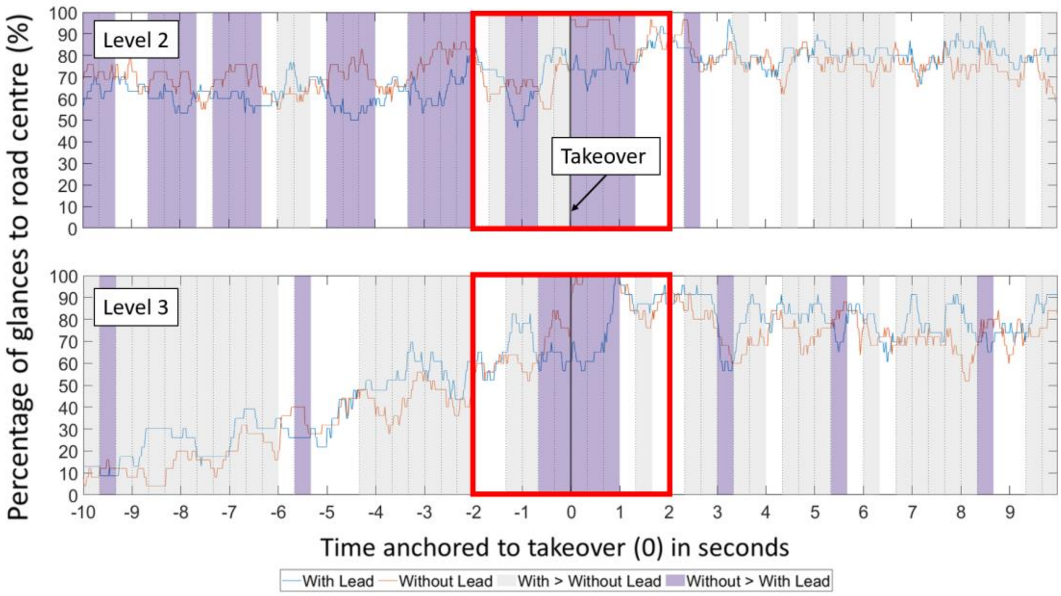

Figure 4.3 Graphical representation of drivers' gaze concentration to the road centre throughout the transition of control

The black line in the middle of the X-axis represents the time of the vehicle automation's disengagement. The shaded areas in the background of the plot represent which sections of the time course of the transition presented statistical differences between the groups. The boxes in red were used to highlight the significant interactions observed in the data that will be further discussed on the paper.

As can be seen in Figure 4.3, during the majority of the time course of the transition process, participants' attention to the road centre seemed to be higher when resuming control without a lead vehicle in L2 (e.g., from -5 to -3.66 s, and from -3.33 to -2s). The pattern is reversed in the last second before the transition of control, where participants in the lead vehicle condition tended to have significantly higher attention to the road centre (M=74.17%, SD=6.83%), when compared with the ones without lead (M= 58.28%, SD=3.83%) [T(19)=7.87, p<0.01]. On the other hand, for the L3 condition, when participants resumed control with a lead vehicle, they tended to have a higher percentage of gaze concentration to the centre of the road. What was unexpected, however, was that the proportion difference is also inverted for this level of automation, as the drivers get closer to the transition of control. For the last 0.66s of the transition of control process, the mean percentage of gazes to the road centre in the with-lead condition (M=62.83%, SD=3.59%) was significantly lower when compared to the without lead condition (M=71%, SD=6.85%) [T(19)=-6.67, p<0.01]. In addition, for the first second after the transition, the without-lead condition had significantly higher attendance to the road centre when compared with the with-lead condition in both L2 [T(19)=-27.68, p<0.01] and L3 [T(19)=-25.73, p<.01].

4.3.2 Gaze fixation analysis

Figure 4.2 showed that drivers on L3 spent the initial stages of the transition process looking away from the road (potentially to the arrows task). To further explore the observed pattern and how drivers concentrate their gaze during the initial stages of the transition, two sets of Kruskal Wallis test were performed, measuring the effect of level of automation and takeover type on the time it took for drivers to make their first fixation on both the road centre and instrument cluster. The results for the time for the first fixation to road centre showed there was an effect of level of automation [H(1)=32.25, p<0.01], where participants in L3 showed a substantial delay on their first fixation to the road centre (M=2.19s, SD=0.97s) when compared to L2 (M = 0.46s, SD=0.92s). There was no effect of takeover type [H(1)=0.1, p=0.75]. As for the instrument cluster, there was no effect of takeover type [H(1)=2.15, p=0.14], and a significant effect of level of automation [H(1)=11.34, p=0.01]. For this AoI (instrument cluster), the effect of the automation, however, is inverted, as participants in L3 were much quicker to make their first fixation to the cluster (M=1.96s, SD=1.13s) when compared to drivers in L2 (M=2.08s, SD=1.59s).

Differences in drivers' shifts of attention were observed based on the conditional probability for a gaze transition between AoIs to happen, using a Markov Chain structure. shows the significant results for the Kruskal Wallis test, measuring the effect of the independent variables (level of automation and takeover type) on each of the possible transitions. The non-significant results are not reported, to improve the readability.

The results reported below (Table 4-1) show that, drivers in L3 were more likely to make erratic transitions to AoIs without returning their gaze to the road centre (e.g., from the vehicle cabin to the instrument cluster). On the other hand, the effect of takeover type, reducing the probability for drivers to shift their gaze from the road centre to the vehicle cabin, suggests that the presence of a lead vehicle does retain drivers' attention to a potential threat, even in higher levels of automation, where the gaze is proven to be more disperse.

Table 4-1 Report of the significant differences in the Markov chain structure for the probability of fixation transitions between AoIs during the transition of control process

Each line corresponds to a possible transition between two AoIs, where origin AoI represents the initial place the driver was looking, and destination AoI represents the location where they shifted their gaze to.

Variable	Origin AoI	Destination AoI	H	P	Mean Probability L2	Mean probability L3
Automation	Instrument Cluster	Vehicle Cabin	(1)14.246	<.001	0.0158	0.1028
Automation	Road Centre	Off Road	(1)5.036	0.025	0	0.0476
Automation	On Road	Road Centre	(1)4.935	0.026	0.3097	0.148
Automation	On Road	Vehicle Cabin	(1)6.354	0.012	0	0.0578
Automation	Vehicle Cabin	Instrument Cluster	(1)11.902	0.001	0.0833	0.3044
Automation	Vehicle Cabin	On Road	(1)9.065	0.003	0	0.0288
Variable	**Origin AoI**	**Destination AoI**	**H**	**P**	**Mean probability with lead**	**Mean probability without lead**
Takeover type	Road Centre	Vehicle Cabin	(1)4.345	0.037	0.0132	0.1042

4.4 Discussion and conclusion

The goal of this study was to evaluate the effect of the degree of engagement with the driving task, and the presence of a lead vehicle, on eye gaze patterns, during a non-safety-critical transition of control from automation. A driving simulator experiment was conducted with two groups of drivers, engaged in Level 2 or Level 3 automation, and eye movement data were used to see how visual attention is distributed between the vehicle and the road environment during different stages of the transition of control. Drivers in Level 2 were required to monitor the road ahead at all times, whereas those in Level 3 were asked to engage in an NDRT.

Results showed that drivers who were less engaged with the driving task (L3 automation) presented a more scattered gaze pattern, with delayed attendance to the road centre, in line with previous literature in the field (Zeeb et al., 2015/2016]), which reported that drivers tend to take time to shift their attention from a NDRT back to the road environment, significantly affecting their information acquisition pattern, as they have a lower time budget to react to the scenario. The more scattered gaze pattern is in line with findings reported by Gartenberg (2014) which suggests that drivers with less situation awareness (L3) are prone to quicker fixations to several information sources, with a high probability of re-fixation, which explains the observed results on the Markov Chain analysis. On the other hand, the presence of the lead vehicle for the transitions of control for the L3 drivers reduced their probability of gaze shifts to the vehicle's cabin, suggesting that, even for a condition with supposedly more erratic gaze pattern, the presence of a vehicle as a potential hazard still raises their concern and attention to relevant information for the takeover process.

A time-series analysis of drivers' visual allocation showed that, in the presence of the lead vehicle, drivers in the L3 condition increased their visual attendance to the instrument cluster, sacrificing glances to the road centre, immediately before the transition of control. This finding is in contrast to the behaviour of drivers in the L2 group, and results from manual driving studies [17], both of which show that drivers focus on the road centre area and lead vehicle during car-following scenarios. Our results suggest that the lack of situation awareness caused by an NDRT in L3 driving may impair drivers' ability to quickly detect and respond to potential hazards after a transition of control, prompting them to seek information from the vehicle HMI for further assistance and Situation Awareness Recovery. Another possible explanation, especially for the L3 scenario, is that drivers may have quickly realised that the vehicle in front was not an imminent threat, as their vehicle was not accelerating towards the obstacle but rather keeping a constant headway. This possible explanation is in line with previous findings from Louw et al. (2018), which highlights the effect of visual looming of the scenario as an important salience cue to draw drivers' attention and trigger their takeover response.

These findings highlight the relevance of both top-down and bottom-up processing during transition from Level 3 automation and stress the importance of providing the correct information on such HMI, at the right time. Future research should consider a better understanding of how the placement of such features in automated vehicles will assist drivers when they are required to resume control and respond to potential hazards. One possible methodological limitation that may have influenced these results is that it was a driving simulator experiment that diminishes drivers' sense of danger in risky situations and has limited motion cues for the vehicle's speed compared to a real-world scenario. Also, the presence of a NDRT as a proxy for L3 driving automation condition may increase drivers' mental workload, and potentially bias the results regarding their gaze behaviour patterns. To account for both limitations, more studies are necessary, considering test track or real-world studies on the way drivers divide their attention, whenever requested to takeover control.

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5.
The effect of information from dash-based human-machine interfaces on drivers' gaze patterns and lane-change manoeuvres after conditionally automated driving

Abstract

The goal of this paper was to measure the effect of Human-Machine Interface (HMI) information and guidance on drivers' gaze and takeover behaviour during transitions of control from automation. The motivation for this study came from a gap in the literature, where previous research reports improved performance of drivers' takeover based on HMI information, without considering its effect on drivers' visual attention distribution, and how drivers also use the information available in the environment to guide their response. This driving simulator study investigated drivers' lane-changing behaviour after resumption of control from automation. Different levels of information were provided on a dash-based HMI, prior to each lane change, to investigate how drivers distribute their attention between the surrounding environment and the HMI. The difficulty of the lane change was also manipulated by controlling the position of approaching vehicles in drivers' offside lane. Results indicated that drivers' decision-making time was sensitive to the presence of nearby vehicles in the offside lane, but not directly influenced by the information on the HMI. In terms of gaze behaviour, the closer the position of vehicles in the offside lane, the longer drivers looked in that direction. Drivers looked more at the HMI, and less towards the road centre, when the HMI presented information about automation status, and included an advisory message indicating it was safe to change lane. Machine learning techniques showed a strong relationship between drivers' gaze to the information presented on the HMI, and decision-making time (DMT). These results contribute to our understanding of HMI design for automated vehicles, by demonstrating the attentional costs of an overly-informative HMI, and that drivers still rely on environmental information to perform a lane-change, even when the same information can be acquired by the HMI of the vehicle.

5.1 Introduction

Vehicle automation, which partially supplants the moment to moment physical control and monitoring of the driving task by humans, is an increasing feature in new vehicles. The implementation of such systems could bring several benefits (Fagnant & Kockelman, 2015), including the extension of driving and personal mobility to impaired or older drivers (Young & Bunce, 2011), or reducing driver-workload, for example, by taking control of monotonous driving tasks (e.g. engaging adaptive cruise control systems in traffic jam and car-following scenarios, see Stanton & Young, 1998).

Despite its promised capabilities, current vehicle automation technology still has a limited Operational Design Domain (ODD), which, when exceeded, requires the human to take over control (NHTSA, 2016). However, there is growing evidence that removing drivers from the decision-making and physical control loops (Louw, Kountouriotis, Carsten, & Merat, 2015; Merat et al., 2019) may lead to a loss of situation awareness (see Endsley, 1995), and impaired perceptual-motor coordination (Wilkie & Wann, 2010), which are both required to safely resume control of the driving task after automation (Damböck et al., 2013; Mole et al., 2019).

One example of a manoeuvre that could be coupled with a transition of control to manual driving is a lane change manoeuvre, which can be challenging, even during manual driving, due to the complexities associated with determining the correct time to change lane, especially in heavy traffic (Gipps, 1986). Previous literature presents an extensive list of theoretical and mechanistic models that consider a wide range of factors that influence a lane-change decision, and its subsequent outcomes (for more details, see a systematic literature review on this topic by Zheng, 2014; and the integrated Lane-Change decision modelling framework, developed by Ali et al., 2021). For instance, Arbis & Dixit (2019) developed a game-theoretical utility model for lane changes, and concluded that the probability of decision conflicts (i.e. increased decision uncertainty, as defined by Shaw, 1979) is directly affected by the characteristics of the traffic environment, such as the proximity of the upcoming vehicles in the adjacent lane. This argument suggests that the challenges imposed by the nature of a lane-change task may already stress drivers' cognitive resources, and this process can be aggravated by automation, if combined with a transition of control.

Results from previous empirical studies in automation support the idea that the introduction of a transition of control during a lane-change scenario can compromise drivers' ability to change lanes safely, and effectively. For example, Madigan et al. (2018) reported that, compared to manual driving, drivers in partial automation took longer to overtake a lead vehicle, whenever a transition of control was required, resulting in shorter minimum headway distances to the lead vehicle. This delayed response was considered to be due to the need for drivers to understand both system behaviour and road conditions, after a transition of control, before overtaking the lead vehicle.

A large body of literature has investigated how supportive information provided by a Human-Machine Interface (HMI) can support drivers during a lane-changing task. In the context of vehicle automation, a number of studies have shown that providing drivers with system-related information via the HMI can support their understanding of the system's behaviour, promoting safer transitions of control (Saffarian et al., 2012; Gonçalves et al., 2017, Stockert et al., 2015; Banks & Stanton, 2016). In-vehicle HMI can be used to provide automation-related messages, as well as information about the road environment, minimising a driver's need to scan their surroundings, to aid with situation awareness recovery, after a transition of control. Several studies (Richardson et al., 2018; Seeliger et al., 2014; Naujoks et al., 2017; Naujoks et al., 2014) have reported that drivers react faster, and more accurately, to takeover requests from automation, when they receive guidance from the vehicle HMI about the surrounding traffic conditions, prior to a takeover.

When it comes to manual lane-change scenarios, Hofmann et al. (2010) report that providing drivers with information about the direction of travel, and the number of lanes to be crossed, in advance of a lane-changing manoeuvre, reduced reaction time to the lane change, accompanied by lower lateral accelerations. Using a linear mixed model on driving simulator data, Ali et al. (2020) demonstrated that supportive information from connected vehicles in the surrounding environment led to safer transitions, with higher time-to-collision and a smoother acceleration profile, compared to the non-assisted lane-change manoeuvres. These studies provide strong evidence that supportive information from HMI may significantly improve lane-change safety in manual driving. However, less is known about how additional information assists lane changes that are required after takeover from automation.

The majority of the studies reported above base their conclusions either on analyses of drivers' subjective responses, in terms of acceptance/perceived usability of the system (Richardson et al., 2018; Körber, Prasch & Bengler, 2018; Beller, Heesen & Vollrath, 2013), or vehicle-based metrics, such as reaction time, and time to collision (Seeliger et al., 2014; Naujoks et al., 2017; Naujoks et al., 2014; Ali et al., 2021; Ali et al., 2020; Arbis & Dixit, 2019). Regardless of the undeniable contribution of these studies, their approach fails to address how decision-making by drivers, in terms of the processing and acquisition of visual information, is affected by the introduction of additional guidance from an HMI, either with respect to automation status, or in terms of the behaviour of surrounding traffic. Ali et al. (2020) found that the use of information about the surrounding environment in the vehicle's HMI significantly changes the way drivers deal with a lane-change task. Additionally, using a drift-diffusion model, Forstmann & Ratcliff (2016) demonstrated that the sequence in which humans sample visual information significantly affects the way they make a decision, in terms of decision time, choice selection, and ratio of correct responses. However, it is still unclear how additional visual information from an HMI affects drivers' information processing during a lane change manoeuvre which follows a transition of control from automation.

Research shows a good correlation between the duration of eye gaze to a particular task, and the level of dedicated visual attention (Carrasco et al., 2011; Posner, 1980). Studies have found that both covert attention and gaze are sensitive to context-specific stimuli, meaning that eye movements are generally drawn towards the visual elements of any stimulus demanding one's attention, at a given moment (Borji & Itti, 2013). Longer gaze times towards a given element are, therefore, generally used as a proxy for human information processing.

Using a simulated car-following study, Sullivan et al. (2012) demonstrated that, during moments of high uncertainty, drivers looked more frequently towards locations with valuable information about the task in hand, such as the speedometer. A meta-analytical literature review by Orquin & Loose (2013), demonstrated that eye movements have a co-causal relation with human decision-making, with humans fixating more on the information that supports the decision they are about to make. This assumption was further supported by the models reported in Krajbich et al. (2013), which were able to predict the decision-maker's choice, and response time, based on the way they distributed their gaze between the different sources of visual information. Therefore, one can argue that, in order to understand how drivers process information when conducting a demanding task immediately after resuming control from automation (such as a lane change), it is important to understand where they direct their gaze at each stage of this process.

In a previous study (Gonçalves et al., 2020), we observed that, during an automated lane change, drivers presented the same general pattern of eye movements as those reported in studies involving a manual lane change (Tijerina et al., 2005; Salvucci, Liu & Boer, 2001). However, our results also showed a significant increase in drivers' vertical gaze dispersion during automated lane changing, with more glances towards the vehicle's HMI, which was placed in the dashboard area, and displayed the automation status (on/off). Our results also indicated that when the same information could be obtained by looking at the road, as compared to looking at the HMI , drivers tended to look more at the road environment, relying less on the HMI. As our previous studies did not systematically control the information given to drivers during the transition of control, it is not currently clear how drivers' gaze is influenced by the information provided by the system's HMI, in such lane-changing tasks.

5.1.1 Current study

The study reported in this paper was funded by the European project AdaptIVe (Grant Agreement No. 610428). Its main objective was to evaluate the impact of different types of information, provided by an automated vehicle's HMI, on drivers' gaze behaviour, and their resumption of control in preparation for a lane-change manoeuvre, immediately after L3 automation (SAE, 2018). In particular, we investigated how HMI messages about system status, presence of traffic in the adjacent lane, and the presence of a guiding arrow advising drivers about whether it was safe to change lane, affected drivers' gaze behaviour and decision-making time during a lane change. The following research questions were investigated:

1. How does the type of information presented on the HMI of an automated system affect drivers' gaze behaviour before changing lane, following a request to take over from vehicle automation?

2. How does the information provided on an HMI affect when drivers begin to change lane?

3. Does the density of the surrounding traffic (e.g. presence of traffic in the adjacent lane) affect drivers' reliance on the system HMI?

Based on previous literature (Seeliger et al., 2014; Naujoks et al., 2017; Naujoks et al., 2014, Stockert et al., 2015), it was hypothesised that drivers would react faster in a given scenario, if information about the system status and surrounding traffic were available via the HMI during the transition. This help from the HMI was expected to be more evident for more challenging decision-making scenarios (higher traffic density), since it was hypothesised that giving drivers more guidance would reduce their uncertainty and decision-making time (Ali et al., 2020). Based on our previous study (Gonçalves et al., 2020), we expected that drivers would have increased gaze towards the information on the HMI, to check the system status immediately after the transition of control (whenever present), but not necessarily rely as much on the information about the road environment (a guiding green arrow). The presence of vehicles in the adjacent lane was hypothesized to increase the frequency of drivers' gaze to the side mirrors, and to the HMI, whenever information about the surrounding traffic was displayed by the system (Tijerina et al., 2005).

5.2 Method

5.2.1 Participants

Thirty drivers (17 male, 13 female), aged between 21 and 60 years (M=35.53, SD = 11.51) were recruited via the participant database of the University of Leeds Driving Simulator (UoLDS), and an invitation shared using social media. Participants had normal, or corrected-to-normal, vision, and held a U.K. driving licence for at least two years (M=13.51, SD=11.17). Ethical approval was provided by the University of Leeds Ethics committee (Ethics no. LTTRAN-054), and participants received £25 for taking part in the study, which took around 2.5 hours to complete.

5.2.2 Materials

The experiment was conducted at the University of Leeds Driving Simulator (UoLDS). The simulator consists of a 4m projection dome with 300° projection angle and an 8 degree of freedom motion system. Inside the dome, a Jaguar S-Type cabin with fully operational controls is installed. The Seeing Machines FaceLab v4.5 eye-tracking device was used to record the participants' eye movements, with an update rate of 60Hz. Inside the simulator's vehicle cabin, a Liliput 7" VGA touchscreen with 800X480 resolution, was installed near the gear shift, and used for a non-driving related, secondary task, described below. See Figure 1 for a representation of the experimental set-up.

Figure 5.1 Representation of the experimental set-up in the University of Leeds Driving Simulator

In this picture, an anonymous experiment participant is driving in automation mode while interacting with the secondary task, presented on the VGA touchscreen. The cameras near the windshield are part of the eye-tracking system.

5.2.3 Experimental design

Each experimental drive contained six separate scenarios in a continuous drive. Each scenario consisted of an automated car-following task, where drivers needed to disengage the automation to perform a discretionary lane change (as defined by Ali et al., 2020), to overtake any slower lead vehicles. A 3X3 repeated measures design was used, with HMI design (No HMI, System HMI, Full HMI), and distance of vehicles on the offside lane during the lane-change manoeuvre (100m, 25m, 15m), as within-participant factors. Each participant completed three drives (one for each type of HMI), presented in a counterbalanced order.

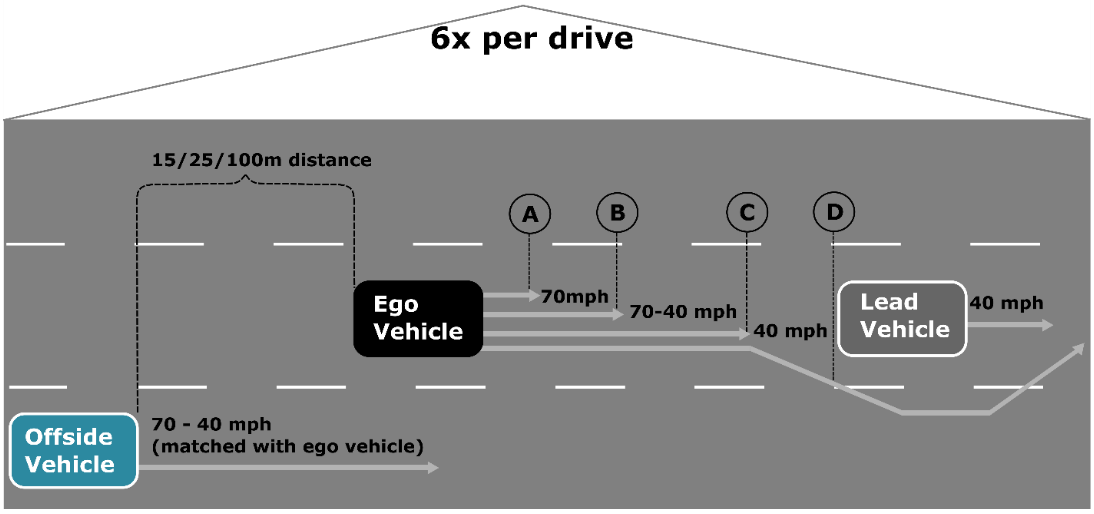


Figure 5.2 Representation of the experimental scenario

> The schematic depicts one of the six overtaking events that occurred per run. Letters A-D represent the stages of the ego vehicle position and automation state. (A) automated system detects the lead vehicle, (B) automated system starts reducing its speed, to match with the lead vehicle, (C) drivers disengage the automation to perform a manual lane change (variable), and (D) drivers' front tyres crossed the lane markings.

5.2.4 Automated driving system

The participant's vehicle was equipped with an automated driving system (SAE level 3; SAE, 2018), which kept the vehicle in the middle of the centre lane, and at a minimum headway of 2s from the lead vehicle. To activate automation, drivers pulled the right-hand stalk when the vehicle reached 70 mph (speed limit) and was positioned in the centre of the middle lane. The automation could be deactivated by either braking/accelerating, turning the steering wheel more than 2° in either direction, or pulling the same stalk used to turn it on. The system was not able to change lanes by itself. Therefore, participants needed to disengage the automation, perform the manoeuvre manually, and then reengage the system.

5.2.5 The distance of vehicles in the offside lane

Each lane change was accompanied by a vehicle in the offside lane, which was driving in the same direction as the ego-vehicle (downstream direction), positioned at three different distances: 100m, 25m, and 15m away from the ego vehicle. Each drive contained two repetitions of these distances, presented in a randomised order (see Figure 5.2). Different combinations of offside distance were tested in pilot studies, and the most suitable set of variables was selected, to suit the needs of this study. Varying the vehicle's distance in the offside lane was used to simulate higher traffic density, and manipulate the challenges associated with changing lanes. Previous studies have shown that a reduced gap between the ego vehicle and the vehicle in the offside lane increases the uncertainty associated with the lane-change task (as defined by Shaw, 1979), and increases task complexity, thus affecting decision-making time (Gipps, 1986; Ahmed et al., 1996; Arbis & Dixit, 2019). This set-up also allowed us to establish if the provision of guidance information by an HMI (that it was safe to change lane) affected drivers' decisions, and whether this was the same for the three vehicle distances (as observed in Ali et al., 2020).

5.2.6 HMI configurations

To understand how drivers' decision-making processes, and gaze behaviours, are affected by information about automation status, and the surrounding environment provided by the automation's HMI, three configurations of HMI design were developed. The visual elements of the HMIs were designed by a project partner, CRF (Centro Ricerche Fiat, FIAT,2021). The **No HMI Condition** contained a blank central cluster, with no information on the system's HMI. There was just a short auditory "beep" which informed drivers when the system was turned on/off. A verbal message, played through the car's speakers, informed the driver when the automation was available. The **System HMI Condition**, outlined in Figure 5.3, included four screens, which informed the driver that the system was on, off, ready and disengaged.

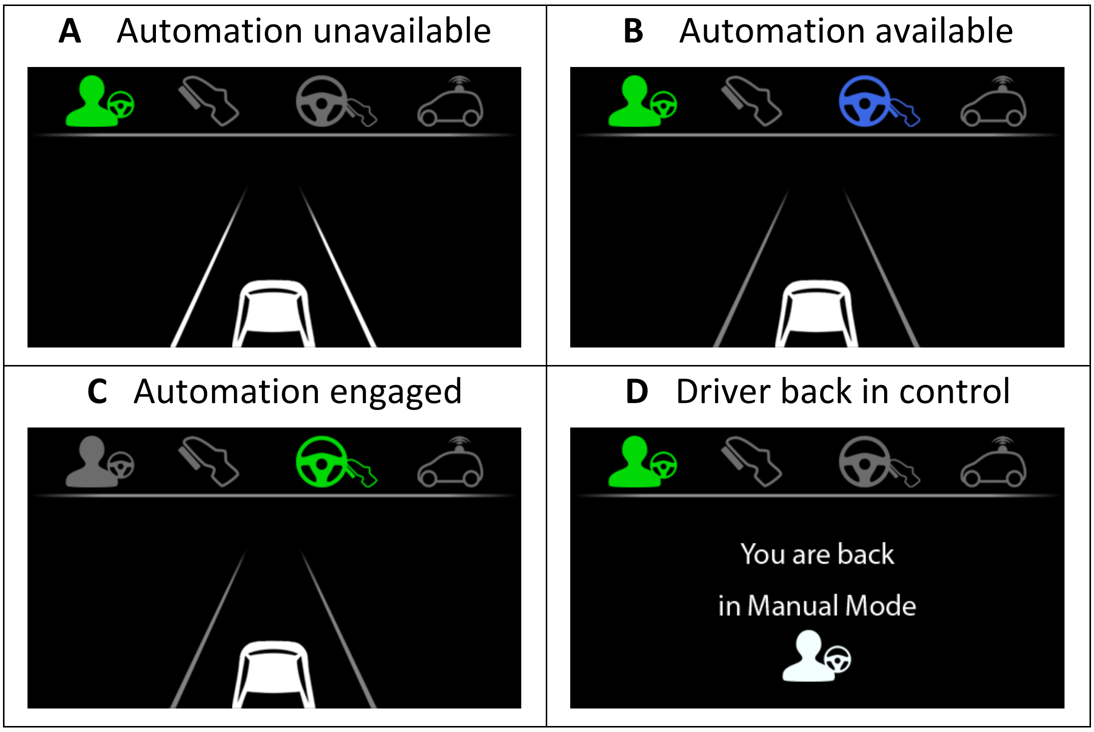


Figure 5.3 - Representation of the System HMI Condition (Designed in collaboration with CRF)

(A) representation of the system in manual mode, with automation unavailable (grey steering wheel); (B) system in manual mode, with the automation available (blue steering wheel); (C) system in automation mode (green steering wheel), (D) message displayed after the driver resumes manual control.

Finally, the **Full HMI** Condition contained the same information presented in Figure 5.3. However, when automation was engaged, additional information was presented to drivers about the surrounding traffic, including the lead vehicle's presence and the approaching vehicle in the adjacent lane (Figure 5.4). Here, once the system perceived a vehicle ahead (6 s headway), a car symbol appeared on the HMI. When the ego vehicle started to brake to match the speed of the lead vehicle (at 2.8 s headway), a lane-change suggestion was triggered by displaying a green arrow, which was used to inform participants that it was safe to change lane, because the offside vehicle was not close enough to trigger a collision, if drivers wished to change lanes. The figure also shows a situation where there was a vehicle close by in the offside lane; however, this never happened during the experimental drives. We introduced this scenario as an illustration during the briefing session and encouraged drivers to judge for themselves whether it was safe to overtake the lead vehicle.

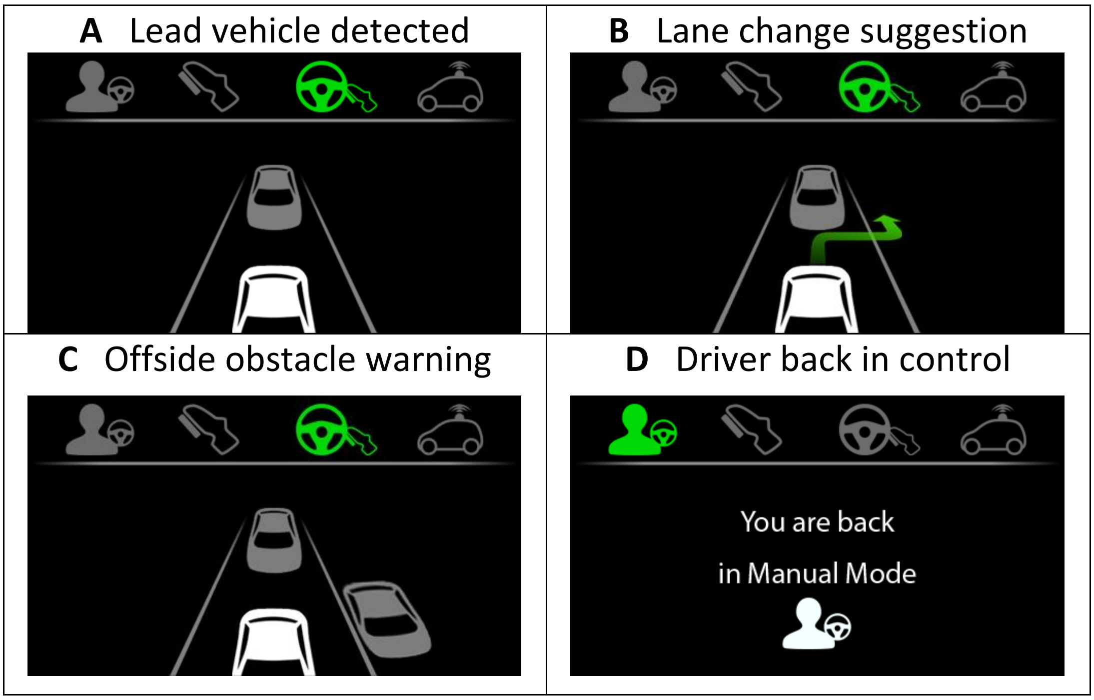


Figure 5.4 Representation of the Full HMI Condition (Designed by: CRF)

(A) represents the automation engaged, with a vehicle detected ahead; (B) represents the lane-change suggestion, whenever the system reached the designated distance to the vehicle in front; (C) represents the fake condition of the unsafe lane change, which was never present on the actual HMI (just on the briefing session) and (D) is the message confirming a successful transition of control.

5.2.7 Non-driving related task (NDRT)

Currently, L3 vehicle automation, as described by SAE (SAE, 2018), permits drivers to engage in other, non-driving related activities, but requires them to be ready to take control, when requested. Therefore, to understand how this ability to engage in other tasks during L3 automation affected lane-changing behaviour during a transition of control, drivers were asked to perform a non-driving related task (NDRT) as soon as the automated driving system was turned on. This visual secondary task, the Arrows task (adapted from Jamson & Merat, 2005), was displayed on a touchscreen monitor, placed near the gear selector, and involved presenting a series of arrows displayed on a 4x4 grid, as shown in Figure 5.5**Error! Reference source not found.**. Drivers had to locate the one upward-facing arrow for each display and touch it as fast as they could. As soon as the up arrow was pressed, the next display appeared. If participants did not find an arrow within 5 s, a new 4x4 grid was displayed. To avoid interference with the HMI information, this version of the task was not accompanied by any auditory signals. To encourage driver engagement with the task, a "score to beat" was displayed on the screen, as shown in Figure 5.5.

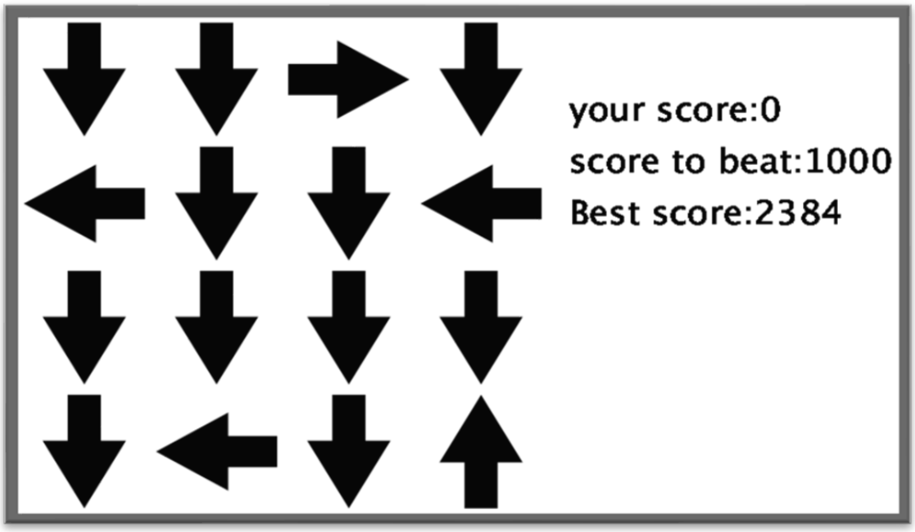


Figure 5.5 Representation of the Arrows task, as it was displayed on the touchscreen near the gear stick

5.2.8 Procedure

Upon arrival, participants were asked to read a description of the experiment and sign a consent form. They were then taken to the simulator dome and familiarised with the vehicle and its controls, including the HMI, and how to operate the automated system. During this briefing session, participants were given the opportunity to practice the Arrows task, both independently and during the automated drive. They were also informed that there was no takeover request, and that the ego vehicle would only brake/decelerate in the presence of a slower lead vehicle. Participants were instructed that, as soon as they felt the vehicle's deceleration, and when they felt it was safe to do so, they should resume manual control of the vehicle, and try to perform a manual lane change to the offside (right) lane. As these were non-critical scenarios, there would be no collision if drivers did not resume manual control, and the vehicle maintained a maximum headway of 2 s, for as long as the automation was engaged. They were also instructed to reengage the automation and resume the Arrows task as soon as they had returned to the middle lane, after overtaking the lead vehicle.

After the briefing session, participants completed a 15-minute familiarisation drive, supervised by the experimenter. The familiarisation drive consisted of a short version of the experimental drives, with one lane-change scenario for each HMI. Once familiarised with the task and environment, the experimenter left the dome. The participants drove the three experimental drives, presented in a counterbalanced order, with five-minute breaks between each drive, during which participants left the simulator dome to reduce any fatigue effects.

5.2.9 Research variables

As described above, the independent variables were the three HMI conditions, and the distance of the vehicles in the offside lane during the lane-change scenarios (offside distance).

To measure how quickly drivers initiated a lane-change manoeuvre following a resumption of control, their Decision-Making Time (DMT) was calculated. This metric has been used in previous eye-tracking studies, to model human decision-making and performance (see examples in Ratcliff et al., 2016; Shaw, 1979; Krajbich et al., 2012, Forstmann & Ratcliff, 2016). For this study, DMT was defined as the time between the beginning of drivers' disengagement from the NDRT to engage in the takeover process (t_{engage}) until the point they initiated the lane-change manoeuvre (t_{action}). t_{action} was also used during gaze behaviour analysis as an anchor point to define the time frame in which the eye movements were extracted from the raw experimental data.

During the data analysis process, we identified that, as it was a non-safety-critical scenario, there was a delay between the automated system's brake (signalising the presence of a lead vehicle to be overtaken) and drivers' interruption of the NDRT, since there was no time pressure for them to respond. It was also noted that not all drivers disengaged the automation in the same way (75% used the steering wheel, while 25% used the stalk). We also observed that some drivers disengaged the automation but continued looking at the road environment before manually performing the lane-change manoeuvre. For this reason, there was no specific point in the experimental condition which could be used to measure t_{action} across all trials. Given the reasons presented above, a MATLAB (version R2016a, MathWorks, 2017) algorithm was developed to calculate drivers' DMT, based on a set of detection criteria, as follows:

- t_{engage} was calculated based on the moment drivers moved their head up from the arrows task display, immediately after the lead vehicle was detected by the automated controller ("A" in Figure 5.2). The assumption for this detection criterion was that drivers stopped interacting with the NDRT after moving their head away from the display and started acquiring visual information to decide when to overtake the lead vehicle. Detection of drivers' head position (whether looking towards the NDRT or the road/HMI) was based on the eye-tracking system's gaze detection quality, since drivers' eyes were not trackable by the system while they performed the Arrows task.

- As the average steering wheel angle input during the manual sections of the experimental drives (outside the lane-change scenarios) was lower than 1° (M = .64, SD=.14), we assumed that any extreme value of steering wheel angle input after t_{engage} would signify the physical engagement with the lane-change manoeuvre. Further analysis found no cases in which drivers moved their steering wheel over 2° without fully committing to the lane-change manoeuvre. Based on this observation, t_{action} was calculated as the time as when drivers made the first steering wheel input over 2°, whether the automation was already disengaged, or not. Figure 5.6 shows an example, for one participant, of how the DMT was calculated.
- The timings for DMT calculation were based on the simulator data output for all participants and trials, regardless of the method used to disengage automation or the experimental conditions. The sampling rate was 60 Hz.

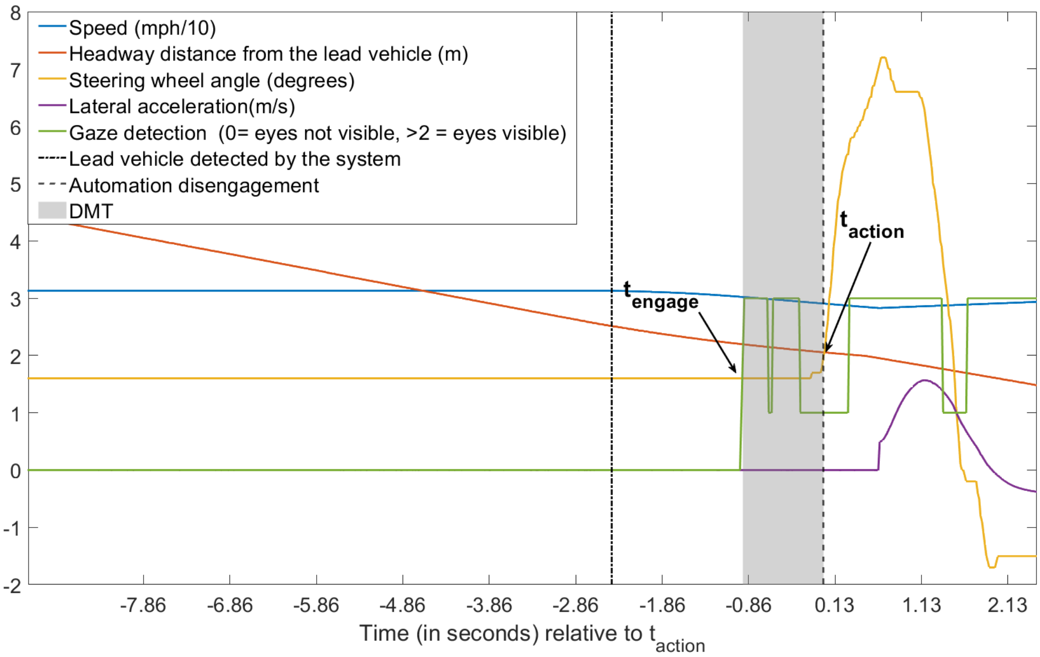


Figure 5.6 Example of how Decision-Making Time (DMT) was calculated for a single participant

> The green line (Gaze detection status) represented the detection of drivers' face in the eye-tracking system. We assumed that drivers were not looking to the road whenever the value in this variable was 0 (meaning drivers' head could not be detected). t_{engage} was detected whenever their gaze detection status was >=2 (meaning that the eye tracker could detect the participant's head, as they were looking upwards). The yellow line (steering wheel angle) was used to detect t_action, as it indicated when drivers were physically engaged with the driving task. The shaded grey area, between the defined points for t_engage and t_action is the total amount of the participant's DMT.

The metric used to analyse drivers' gaze behaviour in the different test conditions (3xHMI and 3x offside distances) was the percentage of drivers' gazes towards five Areas of Interest (AoIs), during the 3 s that preceded t_{action}. This time window of 3 s was selected since not all drivers had the same DMT. Using a relative value for different time windows, would over/underestimate each individuals' gaze percentages, depending on the length of their DMT. A time window of 3s was selected as it included a complete DMT for 87% of participants, while minimising noise caused by non-trackable eye-tracking data (due to the NDRT). Decision-making models, such as those developed by Ali et al. (2019) also support our view that a 3 s time window is suitable to capture the decision-making process in a lane-change scenario.

Based on previous studies (Carsten et al., 2012, Louw et al., 2016; Louw et al., 2017; Louw & Merat, 2017; Louw et al., 2018), five separate regions were defined by the AoIs within the drivers' field of view (Figure 5.7). The centre region was defined as a 6° circular area, centred on the mode of drivers' fixations (see Victor, 2005), defined during the first minute of their experimental drives, which was in manual mode. The other four regions were equally split between lateral and vertical sections of the screen (see Figure 5.7 for a schematic representation of the AoI layout). The top and bottom of the centre region covered the road area beyond the lead vehicle, and the steering wheel/HMI area, respectively, and the two lateral regions covered the wing mirrors and adjacent lanes to the left and right of the central area.

A fixation was calculated as the persistence of drivers' gaze position in a 1° radial area, for at least 150 ms, consistent with the boundaries reported in the literature for dispersion-based fixation identification algorithms (see Salvucci & Goldberg, 2000; Nyström & Golmqvist, 2010). The analysis reported in this paper focused on three specific AoIs, as they were considered to be the most relevant for a lane-change manoeuvre, according to studies of eye-movements during lane changes (Tijerina et al., 2005; Doshi & Trivedi, 2009; Salvucci, Liu & Boer, 2001; Fitch et al., 2012; Chovan, 1994). These were the centre, bottom and right AoIs.

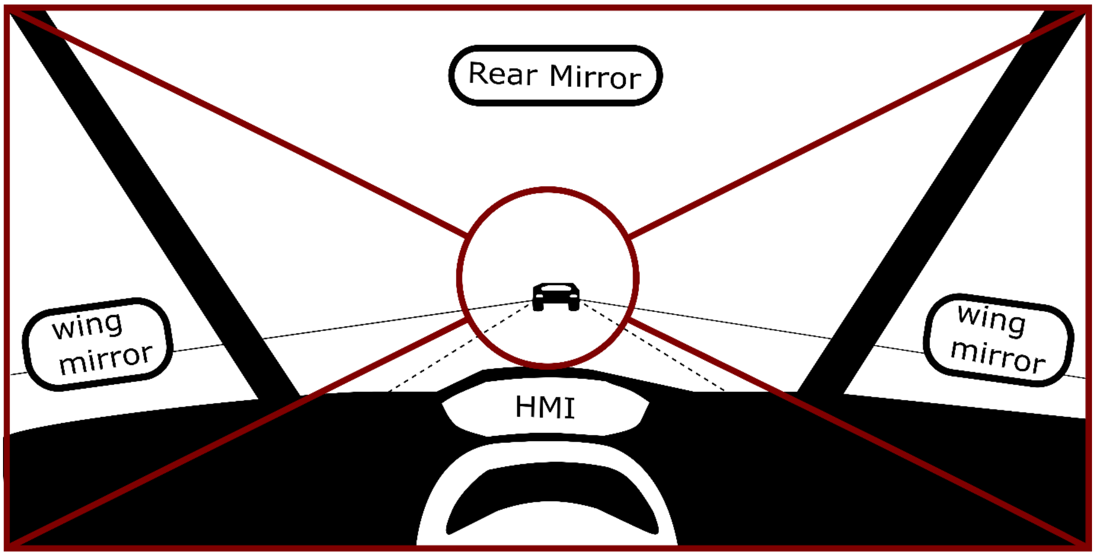


Figure 5.7 Schematic representation of the division of AoIs used in the analysis of drivers' eye movements

The red markings represent the AoIs mentioned above. The black/white drawings represent the visual elements present in the area covered by each of the AoIs. Note that this is just a schematic representation and is not a precise depiction of the elements in the real simulator dome.

5.2.10 Statistical analysis

The data was compiled and pre-processed using MatlabR2016a (MathWorks, 2017) and analysed using IBM SPSS v21 (IBM Corp., 2012). Further analyses were performed using the SKlearn tool in a Python environment (Python Software Foundation, 2020). A Kolmogorov-Smirnov test (Conover, 1999) was used to check for normality and showed that parts of the data had a slight positive skew. Whenever the data was found not to be normal, a logarithmic transformation was applied to rely on parametric tests for the statistical treatment. In cases where parametric tests were not possible, Friedman's test was used as a substitute for a two-way ANOVA. All figures presented are based on the untransformed data, with results based on tests performed on the transformed data.

To filter out the noise inherent in eye-tracking data, all gaze samples containing less than 75% of data points with "good gaze tracking quality", as specified by the eye-tracking software (no gaze estimation based on head position or missing data) were discarded. Two participants did not follow the instruction to perform the Arrows task, and spent the experimental drives looking towards the forward scene. Therefore, their data was not included in the analysis. To exclude other participants who did not adhere to the scenario instructions (e.g. did not perform the overtaking manoeuvre during the experimental drives), outliers were removed from the sample using a criterion of 3x interquartile range (IQR3). An α-value of .05 was used as the criterion for statistical significance, and partial eta-squared was computed as an effect size statistic. Where Mauchly's test indicated a violation of sphericity, degrees of freedom were Greenhouse-Geiser corrected.

5.3 Results

5.3.1 Participants' decision-making time

To test whether the different information from the HMI, and the distance of the vehicles in the offside lane, affected participants' decision-making performance, a Friedman's test was conducted using drivers' Decision-Making Time (DMT), in seconds, as the dependent variable, while HMI condition (No HMI, System HMI, Full HMI) and Offside distance (100m, 25m, 15m) were the independent variables.

Friedman's test results found significant differences between drivers' DMT, based on the HMI condition, and offside distance, during the moment of the takeover [$\chi 2(8) = 15.025$, $p = 0.05$]. Individual Kruskal-Wallis *post-hoc* tests showed a significant effect of offside distance [$\chi^2(2) = 0.953$, $p = 0.0387$], with higher mean DMT values associated with shorter offside distances (15m = 3.09s, 25m = 2.49s, 100m = 1.83s). However, the three HMI conditions were not found to affect this value [$\chi^2(2) = 2.65$, $p = 0.261$]. As shown in Figure 5.8, drivers' DMT was longer when the vehicle in the offside lane was closer, with a similar pattern observed regardless of the level of information from the HMI.

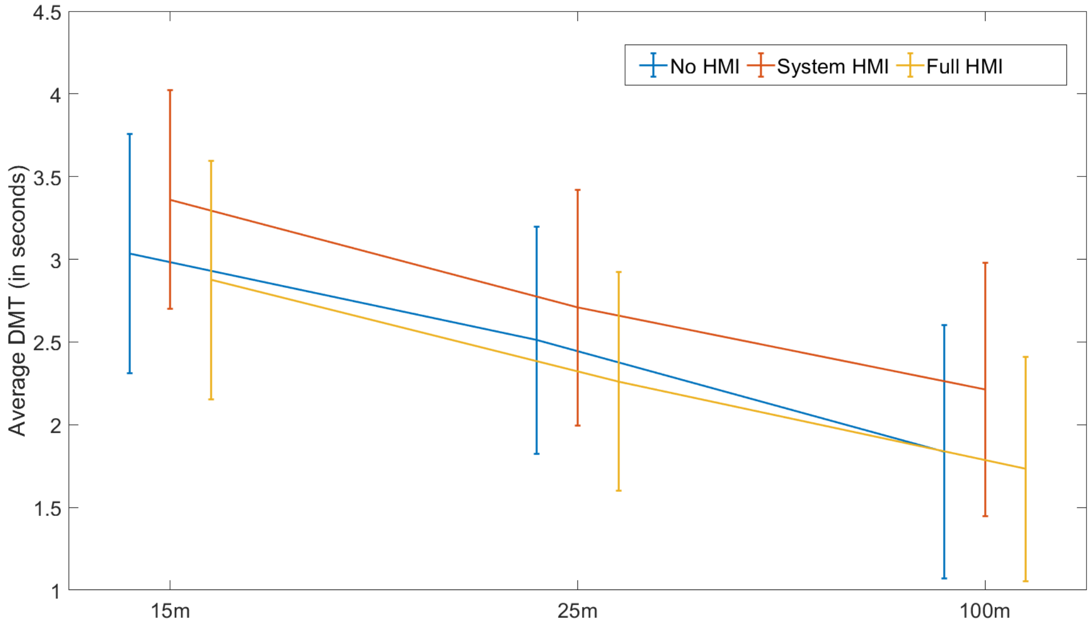


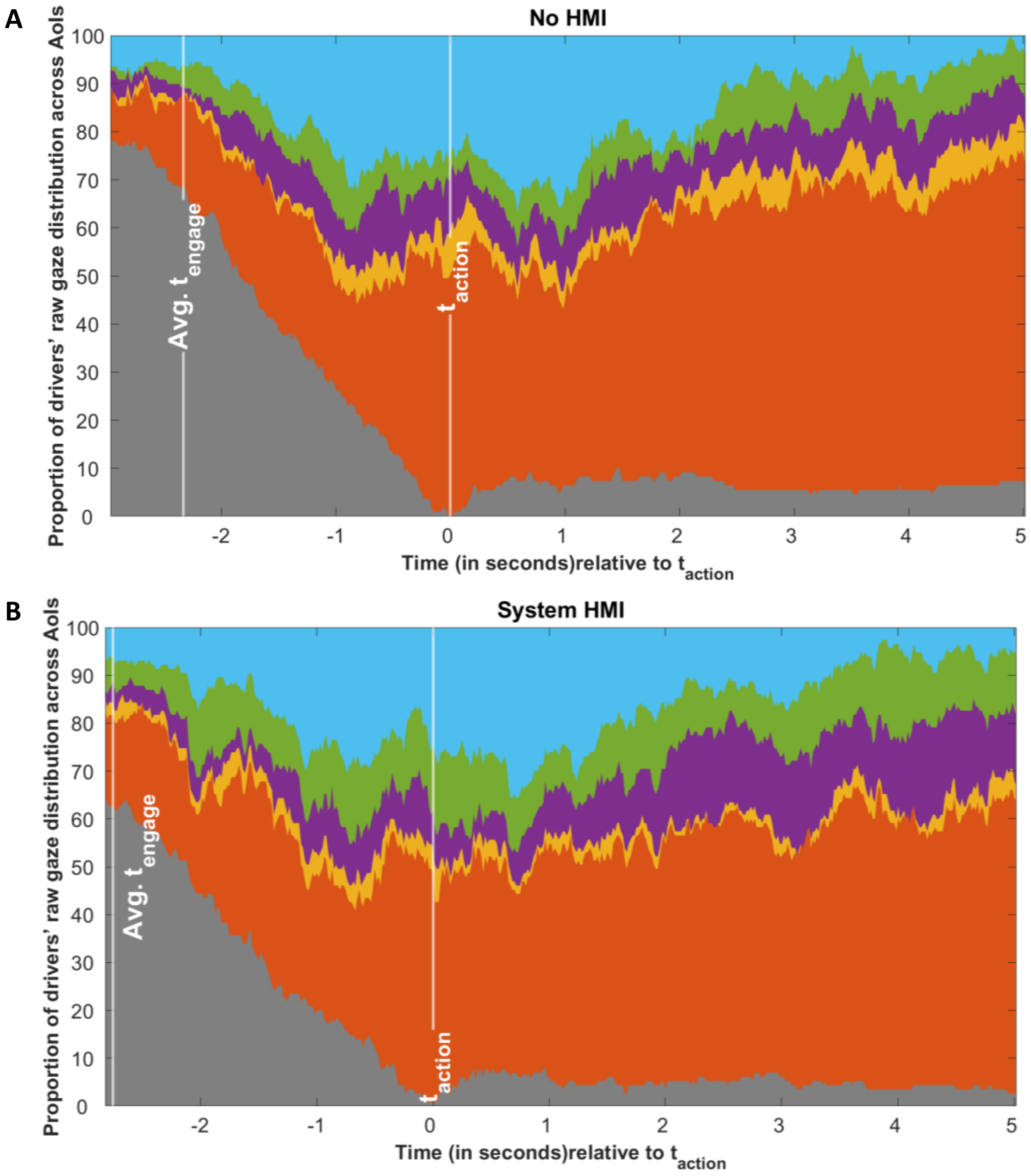
Figure 5.8 Results of Friedman's test on drivers' Decision-Making Time in different test conditions

5.3.2 Participants' gaze distribution

Figure 5.9 shows the proportion of drivers' raw gaze to the different AoIs (see Figure 5.7), for the 3 s before and 5 s after t_{action}. This visualisation shows a similar gaze pattern for the three HMI conditions, after the resumption of control. However, many more glances are seen to the HMI (bottom AoI) when the automation was engaged in the Full HMI condition.

As can be seen in Figure 5.9, for all three HMI conditions, there is a sharp decrease in "Gaze not Tracked" data points during the 3s before t_{action}. As drivers' exact gaze was not trackable during the execution of the NDRT, it is assumed that this large grey area represents the percentage of drivers looking downwards to the Arrows task display.

In terms of percentage of gaze distribution, the pattern roughly follows that observed for manual lane changes (Salvucci, Lyu & Boer, 2001; Tijerina et al., 2005). During the time before t_{action}, which can be associated with what Tijerina et al. (2005) describe as the "decision-making phase", drivers distributed their gaze mainly between the centre (orange) and right (light blue) AoIs, suggesting they were mostly paying attention to the offside lane, and the vehicle ahead, probably to judge whether or not it was safe to engage in the lane-change manoeuvre. After t_{action} ("action phase", Tijerina et al., 2005) a gradual reduction in the percentage of gazes to the right AoI, and an increase in the percentage of gazes to the centre is seen for all HMI conditions, suggesting that drivers were focusing on the vehicle's heading, to manually execute the desired manoeuvre, and change lanes.



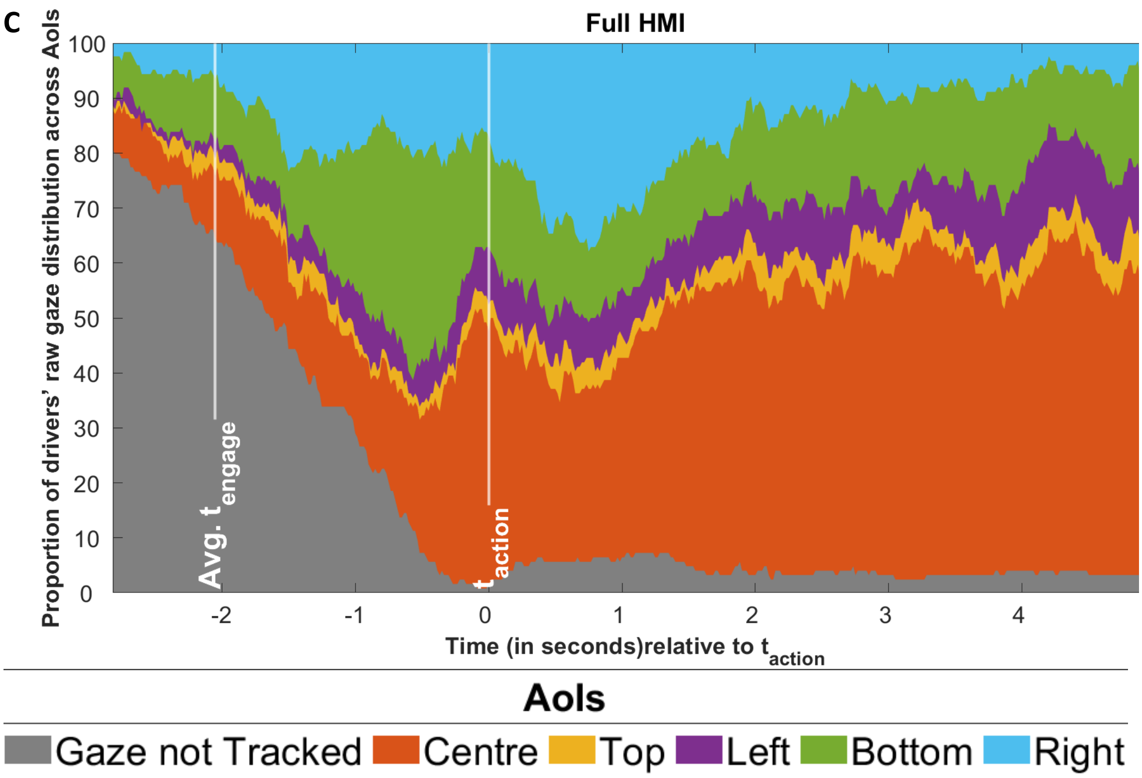


Figure 5.9 Drivers' gaze distribution across the five AoIs. The X-axis represents the 3s before and 5s after t_{action}

The Y-axis shows the percentage of drivers gazing towards each AoI, in a given point in time. The data was captured at a sampling rate of 60Hz. As participants' eyes were not trackable during the Arrows task, all the data points collected during this time on the task were captured as "Gaze not Tracked".

To measure the effect of the HMI information, and traffic densities, on drivers' gaze behaviour, three 3X3 ANOVAs were conducted, one for each of the main AoIs of interest: centre, right and bottom. Each ANOVA had HMI condition (no HMI, system HMI, full HMI) and Offside distance (100m, 25m, 15m) as independent variables, and the percentage of drivers' gaze to the respective AoI, during the 3s which preceded t_{action} as the dependent variable (Figure 5.10).

There was a main effect of HMI condition on the percentage of gaze to the centre AoI [F(2, 258)=6.886, p=.001, $\eta_p{}^2$=.051], where *post-hoc* Bonferroni tests showed this value to be significantly lower during the full HMI condition, compared to the other two conditions. There was also a main effect of offside distance [F(2, 258) =3.458, p=.033, $\eta_p{}^2$ =.026], where drivers' gaze to the centre AoI was higher during the shorter gap condition (15m). No significant interactions were found F(2, 258) =.810, p=.520, $\eta_p{}^2$ =.012].

The ANOVA results for the percentage of gaze to the right AoI showed a main effect of offside distance [F(2, 258)=4.825, p=.009, $\eta_p{}^2$=.036], with a higher proportion of gaze towards the right during the shorter gap conditions (mean = 17.4%, 16.5% and 10.8%, respectively, for the 15m, 25m and 100m, conditions). However, there was no significant effect of HMI condition on gaze to the right, [F(2,258)=.038, p=.195, $\eta_p{}^2$=013], and no significant interaction between HMI condition and offside distance [F(4, 258)=.023, p=.681, $\eta_p{}^2$= .010].

Finally, there was a significant effect of HMI condition on gaze towards the bottom AoI [F(2, 258)=18.852, p<.001, $\eta_p{}^2$=.126], with a significantly higher proportion of gaze towards the bottom as the amount of information from the HMI increased (Full HMI>System HMI>No HMI). There was no significant main effect of offside distance [F(2, 258)=.586, p=.588, $\eta_p{}^2$=.005], and no interaction effects [F(4, 258) = 1.587, p=.119, $\eta_p{}^2$=.028].

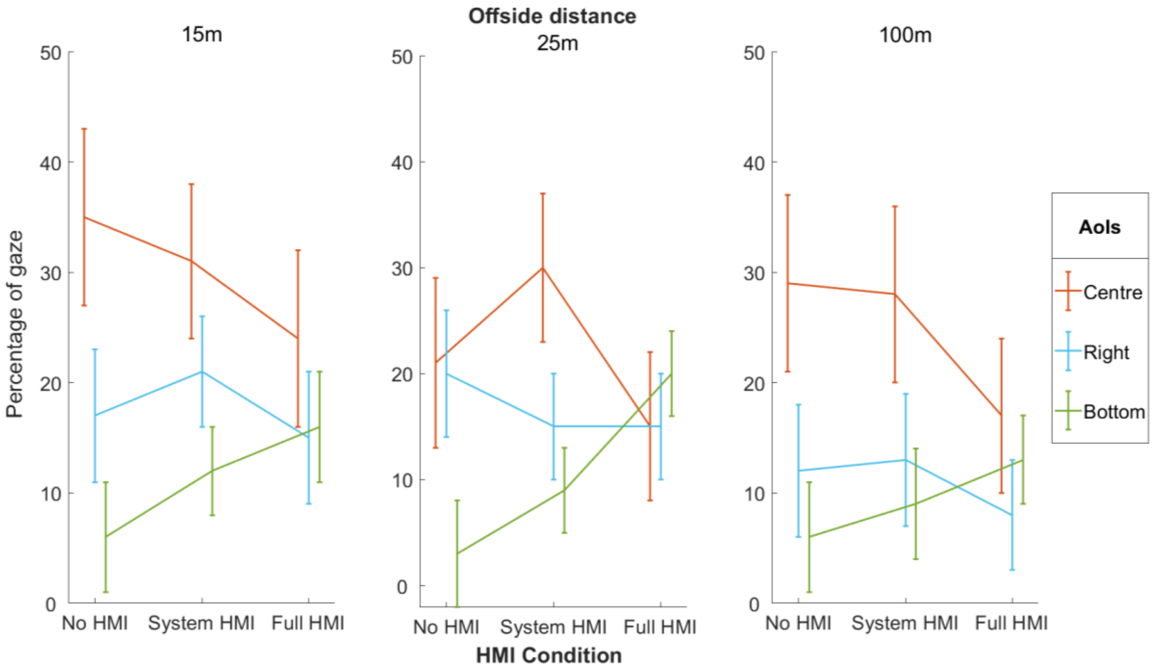


Figure 5.10 Results for the 3 ANOVA tests performed on drivers' gaze on each AoI during the 3s that preceded t_{action}

5.3.3 Gaze behaviour and DMT correlation

As previous literature shows a link between gaze behaviour and the decision-making process (Orquin & Loose, 2013), we investigated how individual differences in gaze concentration to different AoIs affected participants' lane changing DMT, by using a regression model to correlate drivers' DMT with 20 different measures of drivers' gaze behaviour, extracted from the same period of time for which the DMT was calculated (from t_{engage} to t_{action}). These included, the percentage of raw gaze; fixation count; average fixation duration; and time of first fixation, for each AoI. The model also considered the lane-change order (1 to 6) as an independent variable, to account for learning effects.

As the regression contained many predictor variables, and the type of correlation between the model's elements was unknown, we used a random forest (see Segal, 2004; James et al., 2000) machine-learning algorithm for the data fitting. To identify which measures from drivers’ gaze behaviour were correlated with their DMT, separate models were created for each of the HMI conditions, and the predictor weight values of each variable (measures) were used as a proxy for the importance of the information located in the AoI for drivers' decision-making process. The data was split in a 75:25 ratio between training and validation of the models, and the input parameters were tested repeatedly, aiming to reach a better model accuracy. Variables with less than 1% (.01) predictor weight were discarded. To optimize the model output, the hyperparameters (number of variables sampled on each branch of the tree, and number of trees to grow) of the random forest algorithm, were tested using a grid search, and only the combinations of hyperparameters that yielded the best accuracy are reported in this paper.

Results showed that the only statistically significant variable as predictor of DMT (i.e. above .01 predictor weight value) was the percentage of raw gaze towards the five different AoIs. As the order in which the events were presented to the driver (1-6) had no importance as a predictor, we assumed no learning effects in the decision-making process. Table 5-1 contains the three regression model outputs that yielded the best results, in terms of fitting, for their respective experimental conditions. All the regression models had relatively high accuracy (approx. 70%) given the dataset's size, and an average error (ranging from 0.27s to 0.31s, in a task with an average duration of 2.47s), within the boundaries of expected inherent variance in lane-change behaviour data (see Arbis & Dixit, 2019), suggesting that the model is capable of predicting drivers’ DMT reliably, based on their gaze.

Table 5-1 Model performance output and weight values for regression for each HMI condition

The first five lines represent the weight values for the predictor variables (all weights were positive values, and their sum should always total 1). The model accuracy is based on the training dataset, and the values of the average prediction errors are based on the validation dataset. T underlined number in the Full HMI column is highlighted to emphasize the significant difference in this model's output when compared to the other two.

Model variables		No HMI	System HMI	Full HMI
Gaze percentage on AoI during DMT	Right	0.5	0.5	0.55
	Centre	0.38	0.38	0.13
	Left	~0.09	~0.09	0.05
	Bottom	~0.02	~0.02	*<u>0.27</u>*
	Top	~0.01	~0.01	~0.0
Model accuracy		59.15 %	72.69 %	75.29 %
Avg. prediction error		0.27s	0.3s	0.31s

For the No HMI, and System HMI conditions, as expected, the most important variables extracted from drivers' gaze behaviour for predicting their DMT in lane-change scenarios were the percentage of gaze to the mirrors and offside lanes (right AoI) and the road centre (centre AoI). Our data suggests that drivers who focussed on those two main points of the road environment were more likely to make significantly quicker decisions and responses, than those who deviated their gaze to less important areas, such as the top and bottom AoIs.

On the other hand, the observed changes in the predictor weight values for the Full HMI condition suggest that the addition of the advisory green arrows, indicating it was safe to change lanes, affected how drivers divided their attention between the different regions, when more advice was available from the HMI. In this condition, the percentage of gaze towards the bottom AoI gains importance (weight value = .27, compared to ~.02 for the other two conditions), over the percentage of gaze to the centre AoI (weight value = .13, compared to .38 for the other two conditions), becoming the second most important predictor.

5.4 Discussion

The objective of this study was to measure the effect of different types of HMI information, and guidance, on drivers' gaze behaviour and decision-making time, during transitions of control from automation, which occurred prior to a lane-change manoeuvre. The level of traffic density in the offside lane was also manipulated to understand how drivers used different sources of information from an HMI and the road environment, to help with more challenging lane-changing decisions, when traffic behaviour was more ambiguous. A series of regression models were also generated to correlate drivers' gaze behaviour to the decision-making time.

5.4.1 The effect of dash-based information on drivers' gaze behaviour

Results from drivers' gaze concentration to the different AoIs illustrated a higher percentage of gaze towards the bottom AoI, corresponding directly to the amount of information presented on the HMI, at the expense of reduced gaze to the road centre (centre AoI). In the Full HMI condition, gaze towards the bottom AoI (HMI) increased just before drivers' first steering wheel input (t_action), which was immediately before drivers started to change lanes, suggesting that drivers used information from the HMI to help them decide how to act (at least for the Full HMI condition), at the expense of glances to the centre AoI (road centre). This finding is supported by core gaze and decision-making theory (Carrasco, 2011; Orquim & Loose, 2013; Sullivan et al., 2012), which states that humans tend to fixate longer on the information that they are processing. This finding highlights one potential issue with the implementation of overly-informative and complex HMIs, as drivers attend to information presented on an HMI, as a trade-off to glances to the road centre. This issue must be taken into account when designing future vehicle HMIs, because reduced glance time to the road is generally associated with higher crash probabilities (see Harbluk et al. 2007). Of course, these results may also be affected by the novelty of the messages used in this study, and it is important to understand how such gaze patterns might change with longer term use of such in-vehicle systems and interfaces.

Drivers' gaze pattern towards the HMI was not found to be affected by the position of vehicles in the offside lane. This result was not expected, and goes against our initial hypothesis that drivers would rely more on the HMI information, when the scenario was associated with more difficult decisions, e.g. when the vehicle in the offside lane was closer. A look at drivers' attendance to the side mirrors explains this further, showing a significant increase in the percentage of drivers' gaze towards the right AoI, for shorter offside distances. This finding suggests that, for safety critical situations, drivers relied also on their own judgement, on top of the HMI advice. The increased proportion of gaze towards the mirrors for more difficult decisions was expected, and is in line with previous studies (Orquim & Loose, 2013; Sullivan et al., 2012), suggesting that real-time information from the surrounding road environment is more valuable to drivers in more safety critical situations. Since we did not find any difference in the pattern of drivers' gaze to the right AoI (right mirror), across the three HMI conditions, our results suggest that drivers did not use the HMI information as a substitute for the mirror checks, which is typical for a manual lane-change (Tijerina et al., 2005), but rather a complement to it, since both glances to the right and to the HMI were constantly present for the events in the Full HMI and System HMI conditions.

In terms of our regression model, "glances to the right AoI" was found to be the only predictor variable in the Full HMI condition, showing stronger correlation with drivers' DMT than the "glances to the HMI" variable. The suggestion that glances to the side mirrors is the most important predictor of drivers' decision for a lane-change prediction model is consistent with studies on lane changes in manual driving (Doshi & Trivedi, 2009; Salvucci, Liu & Boer, 2001), and highlights the relevance of mirror checks for the decision-making process, even in automated driving scenarios. This similarity in gaze behaviour between automated and manual lane changing was also observed in another lane-changing study conducted in our lab, which did not include different types of information on the HMI (Gonçalves et al., 2020), and supports the argument that drivers tend to rely on information from the road environment, for their decision-making.

Of course, it can also be argued that this mirror-checking pattern illustrates a potential lack of trust in the automated driving system, and our HMI information (Lee & See, 2004), or is due to an automatised, well-learnt, behaviour. It is reasonable to assume that such patterns of behaviour may change after prolonged exposure to a reliable automated system and HMI (i.e. a conditioned learned behaviour, Charlton & Starkey, 2011). Further work is, therefore, needed to observe how prolonged and sustained interaction with such in-vehicle HMIs changes the long-term behaviour of drivers, and their gaze patterns, and how different levels of system reliability and traffic scenarios affect this behaviour.

5.4.2 The effect of dash-based information on drivers' DMT

Drivers' DMT was found to increase in line with the position of the vehicle in the offside lane, with higher DMTs for closer vehicles. This result was expected, and is supports the large body of literature on decision-making theory (Shaw, 1979; Ratcliff et al., 2016), and lane-change manoeuvres (Gipps, 1986, Arbis & Dixit, 2019). Here, the uncertainty associated with a lane-change ahead of a nearby vehicle in the adjacent lane caused drivers to spend longer making a lane-change decision, likely associated with the need to look around more at their surrounding environment. However, the lack of an effect of HMI condition on drivers' DMT goes against results from other experiments in the field of vehicle automation (Richardson et al., 2018; Seeliger et al., 2014; Naujoks et al., 2014; Naujoks et al., 2017; Stockert et al., 2015), which suggest a significant improvement in drivers' performance, with the help of information from the HMI.

This observed lack of a difference for the DMT values for different HMI conditions in this study may be due to our HMI design, which was perhaps not as informative for participants as we had envisaged. On the other hand, the output of our regression models showed that, in the Full HMI condition, there was a strong correlation between "glances to the HMI" and drivers' DMT. This was not the case for the other two HMI conditions, suggesting that the presence of supportive information (i.e. the green arrow signalling a safe lane change) is indeed beneficial for the decision process (supporting the findings from Richardson et al., 2018; Seeliger et al., 2014; Naujoks et al., 2014; Naujoks et al., 2017, Stockert et al., 2015). However, the observed correlation was not strong enough to generate perceivable changes to the mean DMT, based on the experimental conditions alone, as individual differences in drivers' gaze behaviour might have affected the way drivers interacted with the visual information, and therefore, masking the potential effects on their DMT.

The arguments in favour of a more informative/supportive HMI is that a clearer and more direct orientation to the situation, as provided by the HMI, helps the driver to recover situation awareness, and avoid potential accidents caused by delayed or inappropriate responses. However, drivers in the current study were not under pressure to perform a lane-change as quickly as they could (i.e. they were asked to complete a discretionary lane-change). Results from Ali et al. (2020) demonstrated that drivers tend to spend more time, and are more careful in their lane-changes, when there is more information from a vehicle HMI. According to these authors, drivers changed the way they accessed the information, not only checking the mirror and the road centre, but scanning all the information at their disposal. Regarding the current study, this suggests that our drivers may have checked the HMI as a routine, as they expected the information to be there, but also checked the side mirrors, as they are habitually used to, before a lane-change. Therefore, the contributions from the HMI information to drivers' DMT were likely countered by the fact that drivers spent more time to check and process the additional information on the HMI, on top of their standard gaze check routine, which ultimately increased their DMT.

5.5 Conclusion

The data presented here offers new insights for the design of new in-vehicle HMI relevant to automation. Although additional information from such HMI should provide potential supporting benefits, results from this study suggest that excessive HMI information comes at a cost, by attracting drivers' gaze, at the expense of glances to the road environment. Results suggest that although drivers looked at the HMI on the run up to a lane change, they ultimately opted to also "believe their own eyes" and use information from the driving environment to decide when to change lane, looking consistently more at the side mirrors, just before the changing lane, regardless of the HMI condition. Therefore, system designers must be aware that not all information presented on an HMI is a good substitute for that provided by the surrounding environment. Further research is needed to understand what type of information from an HMI is useful (e.g. indicating system status) versus those that are considered superfluous. The value of using other modalities for presentation of relevant information in such scenarios should also be explored. This includes the use of heads-up displays, or spatially congruent haptic messages (Ho et al., 2006), which would allow the system to provide supportive information, without compromising drivers' visual attendance to the road environment.

Regarding limitations of this work, and considerations for future studies, the accuracy of the regression models' output (59.15 % - 75.29%) is clearly limited by the overall sample size of the data, which might compromise the takeaway implications of such analysis. This work has also not considered the importance of other factors known to affect the overall takeover process and decision to change lanes, such as driver experience, trust in vehicle automation technology, and fatigue, as examples. Finally, the lack of agreement between the results from this study, and those of others in this context (e.g. Naujoks et al., 2017), may be due to a lack of time pressure for drivers in the current study, or the use of rather simple messages from our HMI. Further work should, therefore, consider the use of a more informative interface, or a more challenging decision task, to assess the value of such information to drivers.

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6. Applicability of risky decision-making theory to understand drivers' behaviour during transitions of control in vehicle automation

Abstract

This work presents a consideration of the applicability of risky decision-making theory models as a tool to understand drivers' take-over behaviour from vehicle automation, while also incorporating the "Out of the Loop" concept and the process of Situation Awareness Recovery. A methodological discussion is provided, and implications for the processes involved in system design developments are presented. Finally, the paper concludes that the process of evidence accumulation in risky decision-making theory models has strong parallels with the process of Situation Awareness recovery. We argue that evidence accumulation models can be used as a tool to understand what information is used by drivers for achieving safe transitions of control from automation so that this knowledge can be used for a better, and more human-centred design of future in-vehicle interfaces.

6.1 Introduction

Among the human factors-related challenges of implementing vehicle automation, is ensuring safe responses from users during transitions of control. Recent research into this issue forms part of a larger body of research regarding the better design of human-machine interfaces, spanning multiple domains and decades. These challenges highlight an old irony of automation, where the more reliable the automation, the less prepared the human is to react in a time of need (Bainbridge, 1985). This is especially true for higher levels of vehicle automation, which do not require continuous monitoring of the driving task, but still rely on users to resume control, for example, when a system limitation is reached (Level 3. See SAE, 2018 for a complete description of the levels of vehicular automation).

Many recent driving simulator studies, for example, those described by Louw & Merat (2017), have identified that drivers in higher levels of vehicle automation (SAE L2+) are removed from the decision-making and control loops of the driving task, placing them "out of the loop" (see Merat et al.

(2018) for a recent description of the term). This disengagement from the loops is thought to reduce drivers' capacity to react in dangerous situations, increasing the likelihood of collisions.

Many researchers have tried to understand what constitutes a safe transition of control from automation, investigating what factors influence the success of a transition. For example, Gold et al. (2013) demonstrated that drivers' response to an impending collision, following a request for a transition of control, is dependent on the amount of time given to drivers for this response. These authors report that when drivers were given less time to react, they reacted faster, but more erratically, as shown by the vehicle's lateral and longitudinal accelerations. In contrast, when given more time to respond to an impending collision, drivers reacted more slowly but had a more stable response profile.

Zeeb at al. (2015, 2016) have shown that drivers' take-over time and the quality of this take over (measured as vehicle lateral deviation), is linked to their attention to the road environment during automated driving, with higher levels of distraction to other, non-driving-related tasks, leading to a deterioration of take-over quality. However, Louw et al. (2018) suggest that take-over time and vehicle controllability alone are not good predictors of a safe transition of control, but rather the early mitigation of a threat, with earlier transitions of control leading to fewer collisions.

A common limitation of studies attempting to correlate drivers' visual attention with their performance on non-driving-related tasks during automation, is that most investigate the location of drivers' gaze, rather than attempting to understand how visual information, acquired from different sources during automation engagement, affects drivers' resumption of control. While there have been efforts to model the factors that influence drivers' capabilities to takeover control, and how they use the physical and mental resources they need to perform such an action, most have not managed to generate a predictive model, based on gaze patterns during take-overs (Happee et al., 2018). For example, Victor et al. (2018) have reported that some drivers, even though looking to the road centre, still failed to avoid crashes during a transition of control (similar to results also reported by Louw et al., 2017).

Studies in other domains have considered how visual information sampling affects decision making in humans (see Orquin & Loose, 2013 for a complete literature review of these studies). For instance, Fiedler & Glöckner (2012), identified that gamblers shift their gaze towards the gamble they are willing to make, before their decision, and used this information as a predictor of their choice selection.

This paper proposes that the application of decision making theories, and related models, can be used to address some of the gaps in research on user resumption of control from vehicle automation, by providing a quantifiable method of linking the acquisition of specific information from the environment to the probability of a particular response (Orquin & Loose, 2013). Currently, there are only a few studies that highlight the possibility of such a link (c.f. Markkula et al., 2018). In this work, we consider how theoretical models for risky decision-making can be used to study drivers' transition of control in automation by observing their visual sampling behaviour during different stages of the take over process.

We begin with outlining the two theoretical bases of this work: decision-making theory, and the human factors of transitions of control. Thereafter, the two theories will be compared, especially regarding their analogous processes of Situation Awareness acquisition and evidence accumulation. Finally, this paper considers how such an approach can generate outputs that may be applied by presenting a conceptual mathematical model that can be used to fit experimental data regarding transitions of control to understand human behaviour.

6.2 Transitions of control from vehicle automation

This section of the paper aims to define key concepts in the field of human factors of transitions of control, such as the decision-action loop, Situation Awareness, and the issues that are related to this process. With a clear definition of this concept in hand, it will be possible to compare them to the concepts related to the decision-making theory, understanding how they might interact and complement each other.

The term transition of control was described by Louw (2017) 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." SAE (2018) complement this definition with a taxonomy, by outlining how a driver's responsibility varies across the different levels of automation, and a distinction if they were system- or driver-initiated transitions. The need for such transitions of control is partly based on current system limitations, in terms of the technology's operational design domain (see NHTSA, 2016, for a more descriptive definition of the problem), where vehicles cannot operate in all scenarios, and the human drivers are expected to supervise the automation and resume control, whenever a system limitation is reached. However, the inherent problem with such supervisory roles is diminished driving capabilities associated with the relinquishing of control, which his associated with several challenges when drivers are requested to resume control, especially in time-critical scenarios (Louw, 2017). Some of these issues are discussed below.

6.2.1 The decision-action loop

According to many authors (e.g. Young, 2012), manual driving is a task which requires the driver to always be in the information processing "loop", with regards to their interactions with the surrounding road environment, as well as their ability to control and coordinate vehicle manoeuvres, involving steering, acceleration and braking. Thomas (2001) states that the operation of a vehicle is closely associated with constant feedback and feed-forward cycle of human interaction with the task. Here, humans' decisions and actions affect the situation, and this change is perceived once more by the individuals, who orient and adjust their behaviour accordingly. Merat et al. (2018) further complement this logic for the context of vehicle automation (based on the model purposed by Michon, 1985), by stating that there are two distinct loops in manual driving, which can be affected by ceding control to automation: one for motor-control coordination, and another for the several decision-making processes that need to be performed while driving. They suggest "(…) that "being in the loop" can be understood in terms of (1) the driver's physical control of the vehicle, and (2) monitoring the current driving situation (…)" (Merat et al., 2018). It must be noted that both loops continually interact with each other, and drivers must be aware of both their visual-motor coordination (see Wilkie et al., 2008 for a more descriptive definition of the term) and the surrounding environment, to safely maintain control of the task.

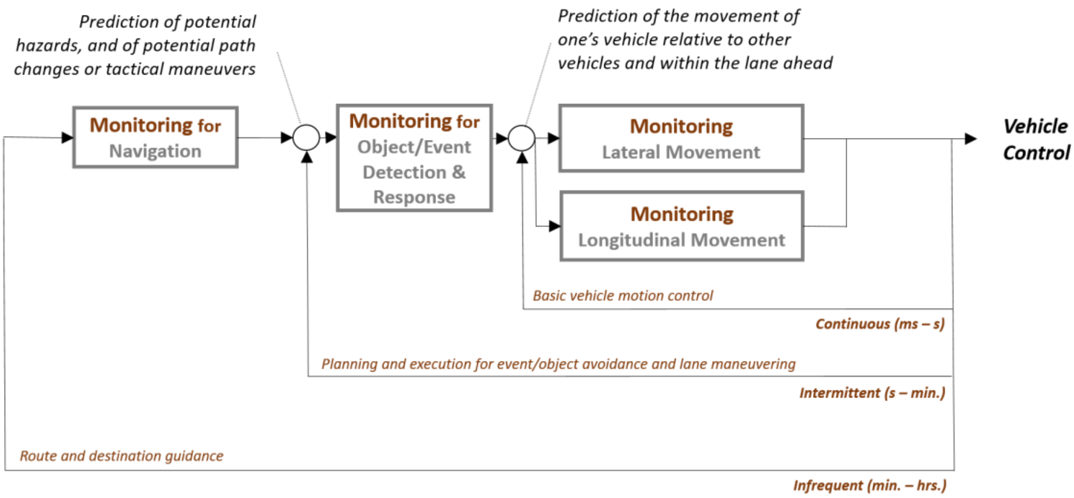

Figure 6.1 Representation of the decision-action loop and drivers' monitoring role in manual control of the driving task (Merat et al., 2019; based on Michon's model, 1985; Copyright © 2019 Springer. Reprinted with Permission of Springer Publications)

6.2.2 Situation awareness recovery

Using driving simulator experiments, Louw et al. (2016), supplemented by previous evidence from Damböck et al. (2013), argue that by removing drivers from the decision-making and control loops, vehicle automation reduces drivers' Situation Awareness (SA; Endsley, 1995), which needs to be re-acquired in order to safely resume control and avoid potentially dangerous situations on the road (Damböck et al., 2013). The definition of Situation Awareness used in this research, and defined initially by Endsley (1988), 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." In short, SA can be divided into three levels (perception; comprehension and prediction), which allow humans to orient their decisions in a particular context and volume of time (Figure 6.2).

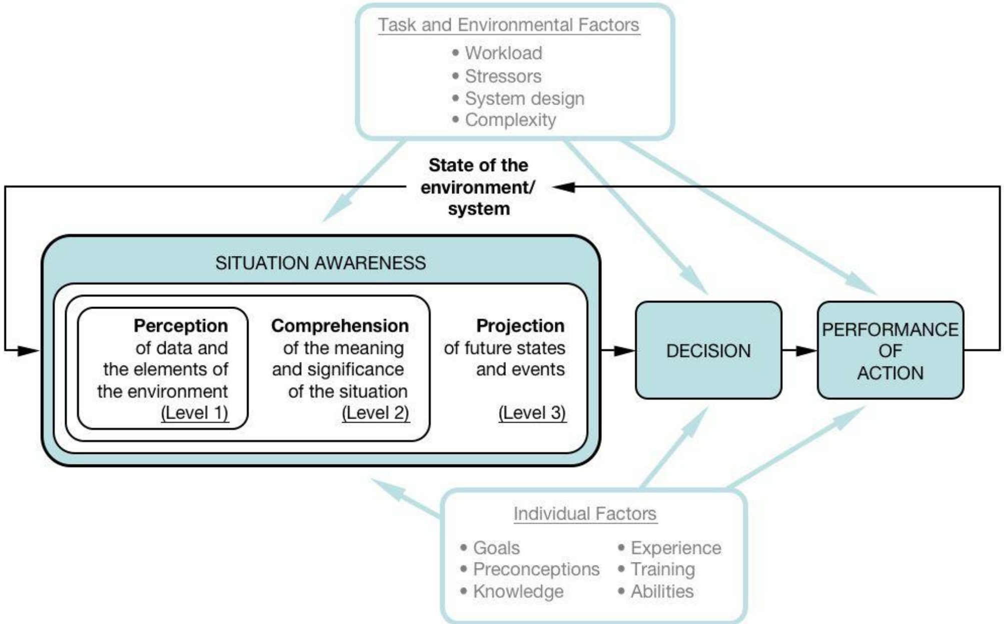

Figure 6.2 Endsley's model of SA. This is a synthesis of versions she has given in several sources, notably Endsley (1995) and Endsley et al. (2000), in Wickens (2008)

The loss of Situation Awareness and its relation to being “out of the loop” have been declared by a number of studies on vehicle automation (Carsten et al., 2012; Ohn-Bar & Trivedi, 2016; Morando et al., 2019), some of which have considered how these concepts are affected by drivers’ engagement in non-driving-related tasks. It is argued that upon a request to resume control from automation, drivers have to move their visual attention from the NDRT, to focus on other sources of information, related to the driving task, to acquire enough SA to take back control of the vehicle. Gartenberg (2014) refer to this process (which is not only relevant to vehicle automation) as Situation Awareness Recovery or SAR. This is described as a visual scanning process with a considerable number of short fixations in different areas, with a significant lag of resumption in tasks, and a high probability of re-fixation to the same information source, more than once. Examples of such a process was observed in Louw et al. (2019), who reported in their driving simulator experiments that drivers who were engaged in a visual non-driving-related task during automation (assumed to induce an OotL state) had a more scattered gaze pattern after resumption of control from a silent automation failure, compared to those who were required to monitor the road environment during automation.

One of the challenges for the human factors community in addressing this problem is that the process of SAR is accompanied by several barriers, called SA challenges (Endsley, 2006). Endsley & Kriss (1995) named several challenges for the Situation Awareness acquisition, such as attention tunnelling, change blindness, stress on operators' (drivers') working memory, as well as the division of the information required from multiple sources, making it difficult for operators to gather all the information they might need in a reasonable amount of time (e.g. see Parasuraman & Riley, 1998). For driving automation, it has been demonstrated that time pressure, or information overload, might affect the quality of drivers' performance. This is thought to be because drivers' attentional resources are continuously stretched by the high demands of the driving task itself, which is aggravated by automation (Goodrich & Boer, 2003), since the driver is out of the loop. The dispersion of drivers' gaze also competes between focused attention to the vehicle's heading (due to a visual-motor coordination, Wilkie et al., 2008) and hazard perception routines, which are generally characterised by an increased lateral gaze dispersion (Crundall et al., 1999). Therefore, drivers not only have to acquire information about the situation in the environment, and the current status of the system (an issue also reported by Endsley, 2006), but also have to recover their visual-motor coordination, which is degraded once you relinquish control from the vehicle (Mole et al., 2019). Many empirical studies show that this need to disperse visual attention to different sources affects drivers' performance, increasing risk of crashes (see Russel et al., 2016; Zeeb et al., 2015; Blommer et al., 2016; Louw et al., 2017; Merat et al., 2014; Gold et al., 2013; Damböck et al., 2013).

6.3 Decision-making theory principles and models

The definition of decision-making adopted in this work was proposed by Edwards (1954), and is defined as follows: "(…)given two states, A and B, into either one of which an individual may put himself, the individual chooses A in preference to B (or vice versa)". This definition was further developed by Simon (1959), who added organised this process into four main stages: 1) definition of the problem, 2) identification of possible solutions, 3) objective assessment of the value of each solution for the problem, 4) choice of the best solution. As human beings, we are continuously making decisions, based on our internal representation of what we should do in every situation, given certain parameters (stage 3). In a driving task, many actions involve a decision-making process. Some examples include deciding: a comfortable car-following distance (Boer, 1999), what gaps we will accept when changing lanes (Gipps, 1986), how we respond to a potential forward collision (Blommer et al., 2017), and whether to disengage from automation (see Markkula et al., 2018, for more examples).

In the context of this paper, decision-making can be defined as the drivers' choice to take-over control of the vehicle or not, and their take-over modality (how do they take-over). When constructing a model for such decision-making, to account for a good or bad decision, in terms of safety, we have as observable output variables the decision-making time (how long drivers took to decide to take-over), decision choice (how they reacted to the given scenario) and outcome (based on the objectives established for the given situation, were they able to achieve this goal?). Yet, there are several kinds of decision-making theory models, which may account for different aspects of human behaviour, and might be useful for certain situations and not others. Edwards (1954) also divided the decision-making theory models into two main spectrums, which their most recent and developed definitions shall be further explained in the later sections of this paper: the rational and risky decision-making models.

6.3.1 Rational decision-making models

The concept of rational decision-making (see Simon (1979) and March (1978) for a more descriptive definition of the term) is based on a metaphorical "thinking man", as a decision-maker. According to Simon (1979) and March (1978), a thinking man can be characterized as an individual by two main conditions: 1) as being capable of acquiring and distinguishing all possible relevant information for the decision in hand; and 2) the thinking man is capable of assigning the correct value of a specific choice, based on their established goal in each decision-making scenario. Based on these assumptions, two individuals would always arrive at the same conclusion, when making a rational decision about the same problem. The only difference between their choices would be personal bias, or what outcome they want from the decision.

Good examples of rational decision-making models can be seen in game theory (Nash, 1950), which posits that all choices made by an individual have a counterpart by a "hostile" opponent (like a chess game). The opponent will focus their actions on maximising their chances of achieving their goal, which is the opposite of the individual's goal. Another example of a rational decision can be seen in the utilitarianism theory, created by Jeremy Bentham and John Stuart Mill in the early 19th century. This theory holds that there are "greater goods" in life, and every moral action can be quantified in terms the outcome of "happiness", and that it is always right to maximise happiness in our choices in life for a “greater good” (for a more complete description of the term, see Mill, 1868). Indeed, rational decision-making processes are utopic in most cases, and their scope for applicability is limited, as everything needs to be quantifiable, such as in mathematical logic problem solutions (for examples, see Bell et al., 1988).

6.3.2 Risky decision-making models

According to decision-making theory, whenever the decision-maker is forced to make a decision without a clear notion of the possible outcomes of their choice, this process is considered to be a risky decision (Edwards, 1954). Models in the risky decision-making theory are based on the assumptions: 1) that not all variables can be accurately, or even wholly, quantified, 2) that humans are not certain about how their actions will affect the environment of the task in hand, and, 3) humans are not aware of are all the variables that they should consider to make their decision. Humans in that situation can estimate, based on their mental models (see Nielsen, 2010 for a description of the term), the probable outcomes for a given task for each possible action that they can perform, and use that information to guide their decision-making. In situations where the outcome of an individual’s decision is not predictable, they need to account for a level of uncertainty as part of their decision-making process. Uncertainty is defined by Shaw (1983) as the inability of the decision-making to assign the correct value of an option, nor predict the outcomes of their decision to the given environment. This uncertainty concept is a key assumption underlying risky decision-making models and is discussed later in this paper. As humans’ mental processing is not directly observable, risky decision-making models can be used to explain human behaviour based on certain assumptions. The most relevant ones are described below:

Evidence accumulation models assume that every decision-maker a priori does not have sufficient information about the situation to make a decision and will seek evidence that will influence their decision towards one of the outcomes known to them. Furthermore, every individual has a personal threshold of accumulated evidence that once reached, causes them to opt for one possible choice, over another (Ratcliff & Smith, 2004). This threshold varied based on a number of factors, including experience, gender, personal attitudes and many others. It must be noted that the rate of evidence, or “drift”, is accumulated differently for every person, which is also influenced by a number of factors. In the field of vehicle automation, Markkula et al.

(2018) have demonstrated how to apply decision-making models based on evidence-accumulation to explain, for example, what information drivers use to decide how to resume control from vehicle automation to avoid an incoming forward collision.

Bounded rationality models, first defined by Simon (1972), which holds that humans can make decisions based on the information available to them. These have similar assumptions to rational decision-making models but differ in that they assume that humans are not capable of considering all the relevant information to make a decision. This can be caused by a lack of cognitive resources, time pressure, or simple lack of knowledge about the presence of a particular source of information. Considering this paradigm, bounded rationality models assume that the decision-maker prioritises certain information over others (randomly or selectively). This prioritised information will most likely bias the decision towards a particular choice, depending on the information sampled, and not only on individual preferences. This kind of model is especially relevant for the transition of control in vehicle automation, as it is assumed that drivers in such situations can be overloaded with large volumes of spatially dispersed visual information, and may not be able to process all the information they would need Examples for such overload can be found in Gold et al. (2013) and Blommer et al. (2017), who show that drivers change their decisions about when to resume control from automation, based on the amount of time they have to react before the automated system reaches its limit. Although, it is worth considering that those authors have only considered visual information, so other factors might also have affected the observed results.

Satisficing decision-making models assume that the decision-maker will not seek the most optimal solution for his/her problem, but instead will make the first decision where the outcome satisfies their needs or goals in the given situation (Wierzbicki, 1982; Parke et al., 2007). This approach was used in studies by Boer (1999), Boer & Hoedemaeker (1998), and Goodrich & Boer (2003), in different scenarios. For example, Boer (1999) demonstrated that drivers tend to have not one specific “ideal car-following distance”, but rather have a satisficing margin, that floats closer or further to the lead vehicle, where the drivers assume to be safe and close enough to be satisfied and refocus in other demands from the car-following task (such as lateral control of the vehicle), instead of actively re-adjust their following distance to a point they would consider to be ideal.

Most concepts in these models are somewhat interchangeable and can be combined in a descriptive or mechanistic analysis. Their relationship with the field of automation will be discussed in the subsequent sections of this work.

6.4 Relationship between human factors challenges and risky decision-making

Based on the two types of decision-making theory models described above, it is evident that the process of Situation Awareness recovery during the transition control from vehicle automation presents several similarities to the risky decision-making theory, which is discussed in the following sections. Merat et al. (2018) stated that drivers re-enter the cognitive loop of the driving task by acquiring sufficient levels of Situation Awareness. In the same way, Ratcliff & Smith (2004) claim that whenever an individual is presented with an opportunity to make a decision, they will need to accumulate evidence that will support the choice they eventually make. This direct comparison shows similarities in the applicability of both the concept of evidence accumulation and SA for those theories with the same purpose, which is to understand how humans use the information to react to a given environmental condition and achieve their desired goal. Figure 6.3 presents a schematic representation of the proposed relationship between the two theories.

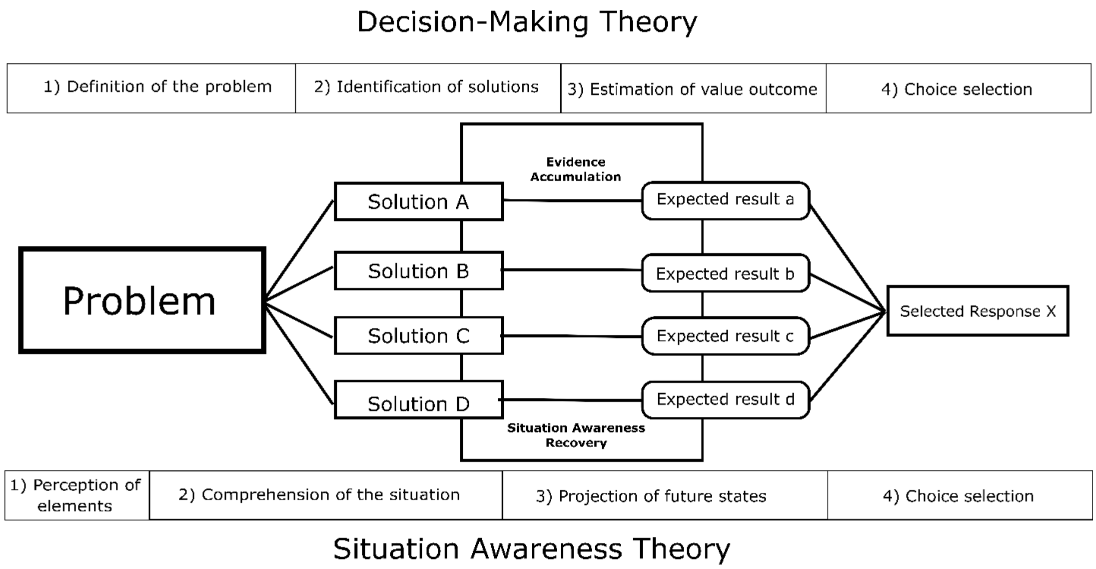

Figure 6.3 Representation of the relationship between SA and decision-making theory

As mentioned above, decision-making theory holds that the decision-making process is composed by four steps: 1) define the problem, and understand its characteristics; 2) formulate/generate possible solutions for the given problem; 3) estimation of the value of possible outcomes; 4) selection of the outcome with the highest value for the given problem (see Simon, 1959 for a better description). Endsley (1995) divided the SA into levels, in a way that the individual needs to 1) identify the elements in the environment, 2) comprehend their meaning, and how it shapes the situation in hand, and 3) orient how those elements can be interacted with, in a way that is possible to predict what can be the outcomes of their potential actions. According to Simon (1957) and Edwards (1954), a decision can only be made if there is a clear notion/definition of the value of each solution to the upcoming problem, and that to achieve this, the decision-maker accumulates evidence that assigns the correct value to a particular option, reducing the decision-maker's level of uncertainty (Shaw, 1982). Observing the same phenomenon through the lenses of the SA theory, we can understand that the comprehension of the problem (in the case of this work, a request to transition control) and their possible solutions as level two SA. The process of assigning value, or expected outcome of possible action in order to make the appropriate decision can be directly linked to the level three situation awareness, or projection of future states. In this framework, it can be assumed that the process of moving from level two to level three SA can be directly compared to the process of accumulation of evidence, which is simply the reduction of uncertainty about the outcomes of a possible action to a given scenario.

The arguments presented in the previous section showed that barriers, called SA challenges (Endsley, 2006), impede an individual's ability to acquire all the sufficient levels of SA they need to make an optimal resumption of control from automation (see Parasuraman & Riley (1997) for an example of such phenomenon). Analysing the challenges imposed to an individual to resume control from automation through the lens of decision-making theory, a similar problem is reported by Edwards (1954) and Simon (1957) who say that an entirely rational decision is utopic. The authors believe that barriers imposed by the scenario, such as time pressure and bounded rationality, forces the human decision-maker to deal with uncertainty, by making assumptions about certain conditions about the environment, based on their expectations, and, thus, adopting a risky decision. As examples relating to resumption of control from vehicle automation, Blommer et al. (2017) and Gold et al. (2013) showed that drivers have an increased probability to "just brake", instead of both braking and steering, whenever they had limited time to respond to the scenario. The authors noted that the scenario exceeded drivers' abilities to cope with the situation and to perform the ideal action. These two examples can be translated in the risky decision-making theory as satisficing decision-making actions, where even if it was not perfect, it was the best they could do with the information they had, opting to make a simple reaction to the scenario.

Based on the arguments presented above, we believe that risky decision-making theory is a suitable candidate to model the process of the take-over of control from vehicle automation. The application of decision-making theory can complement the existing studies on the transition, as it can be used to understand the relationship between the information sampled by drivers and their subsequent behaviour. Practically speaking, this approach complements the current studies in the field by providing robust mathematical models that assign causality between evidence accumulation and decision (see Orquin & Loose, 2013), which are not commonly linked to the situation awareness theory. It is now essential to evaluate how this theory can be applied and implemented to better describe driver behaviour during transitions of control.

6.5 Using decision-making models to orient drivers' decision-making

Sivak (1996) stated that vision is the most important of the five human senses for driving, but yet, it is not suited to dealing with multiple demands at the same time. For this reason, drivers need to prioritise certain visual information over others to perform a transition of control (for more details about this process, see Goodrich & Boer, 2003).

According to Orquin & Loose (2013), visual attention and decision-making are tightly coupled, since a driver's risky decision-making is continuously biased by whether or not they attended to relevant visual information available to them. In their literature review, the authors found a co-causal relationship between visual attendance to information and the occurrence of specific choices, in a discrete decision-making scenario. As part of a meta-analysis, the authors analysed several decision-making tasks that used eye-tracking data as a dependent variable. They concluded that an individual's gaze fixation on certain essential information could predict their upcoming choice in a discrete scenario, suggesting that the selective attention of drivers may bias their decision-making. Such an approach may also be applied to analyse drivers' response capabilities in a take-over scenario, once a take-over reaction is nothing more than a selective response to a particular scenario condition.

The arguments above support the possibility of modelling the relationship between different gaze allocation strategies and the probability of yielding specific responses to the take-over control scenario (based on the studies reported by Orquin & Loose, 2013). This approach would inform system designers about which information should be scanned with higher priority, to yield a higher probability of safe and timely responses to different take-over scenarios. This information could be used to create HMIs that guide drivers towards making decisions that result in safe outcomes. For example, indicating where drivers should focus their attention on a successful transition of control could help avoid an impending collision, as suggested by Louw et al. (2017).

6.6 Formulation of a take-over model

In previous sections, it was discussed theoretically how evidence accumulation models can be applied to understand and predict drivers' take-over behaviour. Evidence from previous literature suggests that inputs from eye movements to the models can create a robust way to understand drivers decision-making process. This section of the paper describes the process of formulation of a mathematical model that can be applied for data fitting suited for the process of transition of control in vehicle automation, based in the elements discussed above.

According to Wagenmakers et al. (2008), evidence accumulation models use real data from experiments to estimate how the process of information acquisition for every individual participant leads to their decision. It receives as the input variable response times (*t*) and choice selection (*p*) of every individual, and based on the individual differences across data samples, they can draw assumptions based on probability distributions of how humans make decisions. According to the authors, and many others in the field (see Ratcliff et al., 2004 for a more descriptive explanation about evidence accumulation models), the main estimated parameters in this kind of model are:

- Mean drift rate (*v*), or how quickly evidence is accumulated towards the decision.
- Boundary limit for the decision (*a*), or how much evidence needs to be accumulated for a decision to be made.

- Previous knowledge or information that may speed up the decision process (*z*), also known as bias.
- Inter-participant variability (*s*), which assumes that different people have faster/slower processes of evidence accumulation.

Figure 6.4 shows how all those variables are fit together in a graphical representation of the model and how the parameters are estimated. It is now necessary to understand how the context of the transition of control and situation awareness acquisition can be translated in this kind of model, and also how data related to visual attention allocation can be used to generate more accurate descriptions of drivers' decision-making behaviour.

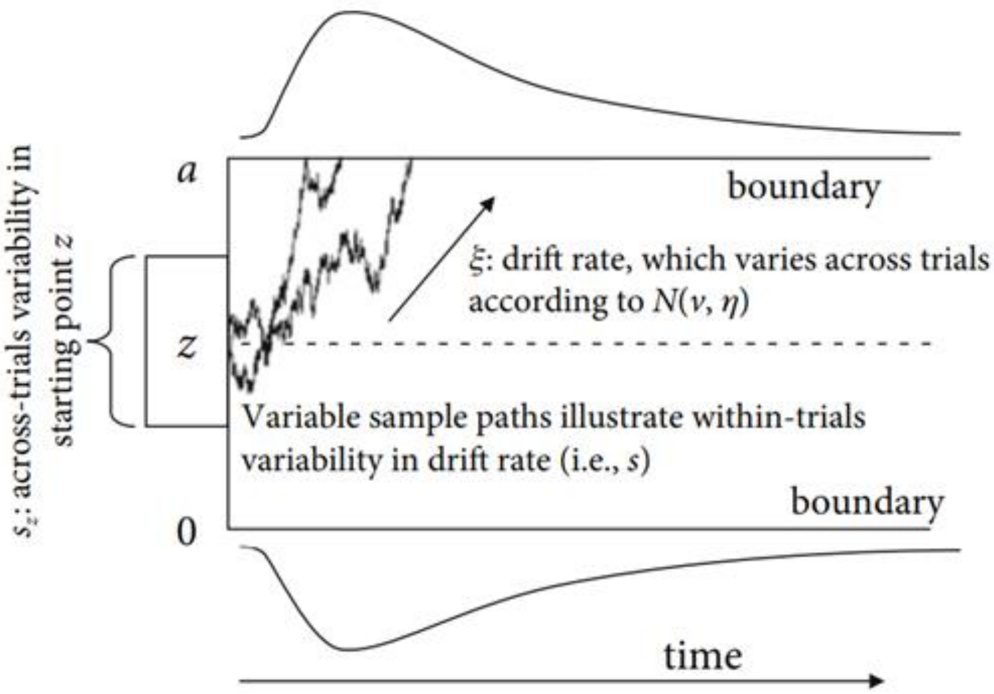

Figure 6.4 Graphical representation of an evidence accumulation model. Source: Ratcliff et al. (2004)

As already said before, the process of situation awareness acquisition can be directly translated as the process of evidence accumulation, in a way that drivers have as their primary goal to safely recover manual control of a vehicle, and will sample information about the multiple options they have to do so, until they reach a point that they are confident enough about one specific option and engage in the task execution. As the situation awareness acquisition process is mainly defined as a visual task (Gartenberg, 2014), and the process of transition of control is mainly constrained by bounded rationality (for examples, see Endsley, 2006), it is possible to assume that different sample patterns would inherently bias the accumulation process, leading to both different response times, and probability of certain response to happen. With this argument in mind, it is then necessary to insert in the model a variable related to gaze allocation over time, which controls how much evidence can be accumulated over time, based in where the drivers are looking (drift rate).

Since this paper describes only a proof of concept for the theory presented above, we opted to develop an adapted version of a linear ballistic accumulator model (LBA; Brown & Heathcote, 2008). This technique was chosen due to its simplified math (easy to explain) and low computational power requirements for its implementation. Future studies might want to consider more robust models, which includes more explanatory variables (eg. drift-diffusion models). The LBA model is an evidence-based decision-making model, which assumes that the process of evidence accumulation related to one possible choice is independent of the other, in a way that sampling information that leads towards one decision would not affect the probability of other option to be chosen. The second assumption of the model is that there is no internal variability or noise in the process of evidence accumulation. For every sample, it generates a linear function between evidence and time. The differences in the response profiles can be only observed by across-participants differences (Dokin et al., 2009).

The flowchart below (Figure 6.5) is the conceptual representation of the proposed model, where drivers after receive a take-over request would sample for visual information, in a goal-directed top-down approach, to accumulate evidence about a possible solution to the task. This evidence would be combined with their previous information about the situation (current SA levels) and their personal bias and would accumulate until it reaches a threshold of satisficing levels, triggering the execution of an action. In this scenario, different sources of visual information would lead to a different drift rate, causing variability in drivers' take-over time. In this process, every possible decision is calculated and modelled separately.

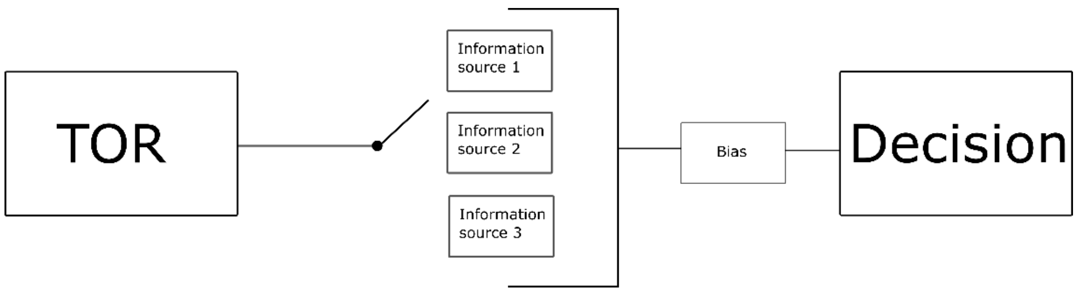

Figure 6.5 Theoretical representation of the proposed model

In terms of calculation, the purposed formula assumes that take-over time (tot) is the sum of the total time drivers spent gazing towards the n different sources (i) of information. Also, the process of accumulation of evidence is defined as the sum of the time drivers spent looking at each information source (t_i), times a constant, which indicates the drift rate, related to each specific information source (v_i). See below the two equations that define the base formula of the model.

Equation 6-1 Formulation for the take-over decision-making model

ToT is the take-over time; t is the time drivers spent gazing towards each information source i; z is drivers' previous knowledge about the situation and personal bias; v is the drift rate for every information source; a is the estimated threshold for the decision-making, and s is the ratio for individual differences.

$$1)\ ToT = \sum_{i=1}^{n} t_i$$

$$2)\ a = z + \left(\sum_{i=1}^{n} t_i * v_i\right) * s$$

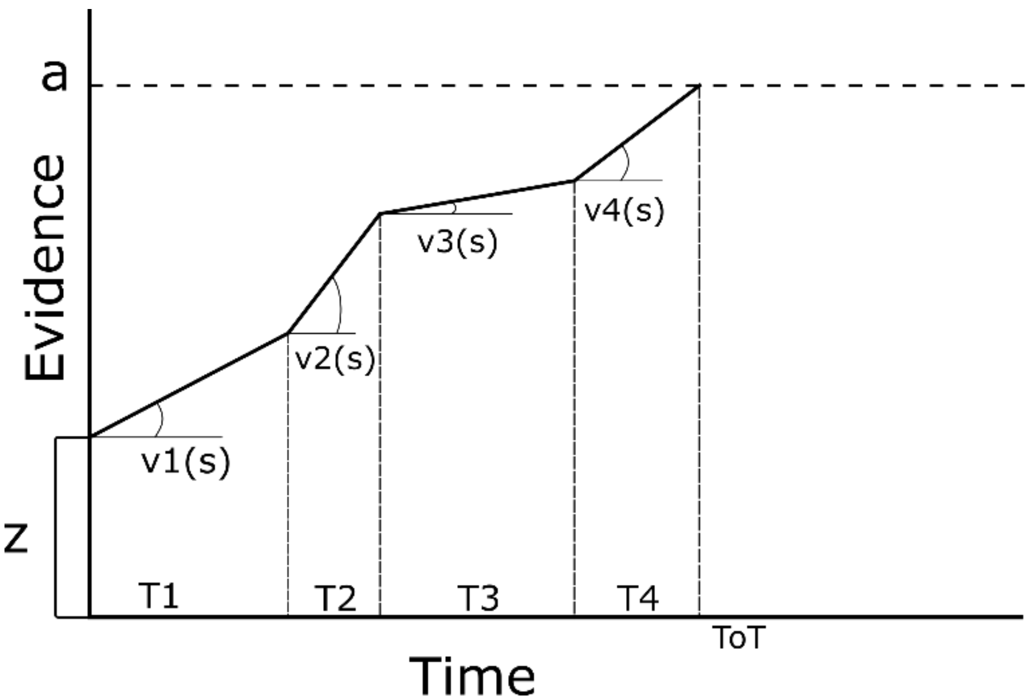

Figure 6.6 Graphical representation of the output from the proposed model

With this approach, it is possible to estimate how valuable certain information source i is for the decision-making process, assuming that it would affect drivers' decisions in the same way. As for the assumptions of the model, 1) it assumes that the process of information acquisition is constant and linear, and does not account for information saturation of one source, nor to noise on the process of information acquisition; 2) it assumes that every option is computed individually, and not in a conflicting way, as a drift-diffusion model would (Ratcliff et al., 2004); 3) it assumes that drivers are in time pressure, in a way that they would perform the decided action as soon as they decided what to do, as mind-wandering and non-decision-making related data would add noise to the model.

6.7 Conclusion

The primary aim of this paper was to assess the feasibility of applying risky decision-making theory models to understand drivers' take-over behaviour during transitions of control from vehicle automation. A secondary aim was to explain how decision-making models could be implemented by system designers as a tool to understand human behaviour and create products that better suit driver needs.

The initial sections point out similarities between the theories on SA and risky decision-making, which makes them comparable and applicable for similar purposes. The main points of proximity between the two theories include the concepts of evidence accumulation and level three situation awareness, respectively, to account for how humans make a decision in a given scenario. We also proposed that models that correlate vision and decision-making modality as a causal factor could be used to identify which information, once sampled, can increase the probability for drivers to perform a supposed "optimal response". In conclusion, we propose that decision-making models, based on evidence accumulation, can be used in HMI design, to enhance drivers' acquisition of certain essential information and, thereby, optimise their take-over performance. For example, if we know how drivers sample visual information before an optimal response, and we use this knowledge to design HMIs to reproduce this behaviour in other drivers in similar situations, then we may increase the probability that they respond similarly.

As for limitations and future directions, this work is chiefly a theoretical consideration and lacks sufficient evidence to defend the real value of the application of decision-making models in the design process for humancentric vehicle automation systems. Empirical studies are required to evaluate how well decision-making models can predict drivers' take-over modality, and whether, if certain information is highlighted in the system design, drivers' performance in take-over scenarios can be enhanced.

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7.
Evidence-accumulation model to predict forward collision reactions in a conditionally automated vehicle using drivers' gaze

Abstract

This paper reports the development and testing and validation of a single-alternative evidence-accumulation model to predict drivers' reactions to a forward collision events in a conditionally automated vehicle. The main source of human input for the model is the drivers' gaze, which is believed to affect drivers' decision and safety outcomes of their reactions. The model also describes the parametrization of the model, and methods to simulate drivers' gaze on Monte Carlo simulations, used for the model fitting. In the end, a discussion is raised about the importance of different information sources for a safe transition of control in a safety-critical forward collision scenario.

7.1 Introduction

This paper describes the development of a single-alternative evidence-accumulation model tailored to predict drivers decision-making time during safety-critical transitions of control from conditional automation (SAE, 2021). The model developed in this study used drivers' gaze data as an input value to control the evidence accumulation process that led to the drivers' decision. The model's concept and parameter estimation methods are presented and its results and theoretical implications to the field will be discussed. The following section of the paper will present the theoretical background that leads to the research gap addressed by the study.

7.2 Background

7.2.1 Transitions of control and situation awareness recovery

Automated vehicle (AV) technology, capable of removing partially or totally the human from the driving task, has been rapidly evolving over the last ten years. Previous research made several predictions regarding the advantages provided by AVs, such as removing human error as the cause of crashes and reducing fuel consumption and traffic jams (see Fagnant & kockelman, 2015). However, as the state of the art on commercial AV technology is still unable to fully address all the challenges imposed by the driving task, humans are still required to take over control whenever a system limitation is reached. This issue is especially critical in what is defined as conditional automation level (SAE level 3; SAE, 2021), which is a transitory step towards the full automation (SAE level 5) that allows the driver to remove their attention from the driving task, but still requires them to take-over control whenever a take-over request (TOR) is issued.

Merat et al. (2019) describe in their theoretical paper that as the drivers relinquish control from the automation, they remove themselves from a constant decision-action loop needed to conduct a safe driving task. The removal of the driver from the loop is related to their loss of situation awareness (S.A., as defined by Endsley, 1995) due to a lack of active engagement with the driving task. Merat et al. (2019) also affirmed that drivers need at least sufficient levels of S.A. about both the system and environment to manually control the vehicle after a transition. To achieve these sufficient levels, Gartenberg et al. (2014) describe the process of S.A. recovery as a mainly visual task, where the drivers generally focus their attention to specific sources of information to fill the gaps in their current mental model, in a goal-oriented approach.

The problem inherent to the S.A. recovery process is that the driving task is very challenging, requiring the driver to acquire information from different sources in a short amount of time. Endsley & Kiris (1995) pointed out several challenges for an automation operator (driver) to recover situation awareness after relinquishing control to an automated system. Some of the most prominent issues related to S.A. recovery are attention tunnelling, change blindness, and limitations on humans' working memory capacity. The barriers imposed by the transition of control might exceed drivers' capabilities to acquire the ideal amount of information to perform an optimal response to the given scenario (Goodrich & Boer, 2003). Gold et al. (2013) provided evidence of the barriers imposed by the transitions of control, when reported higher crash probabilities and higher lateral acceleration on transition scenarios with shorter times for drivers to respond to the risky transition of control.

7.2.2 Risky decision-making and selective information bias

Due to the barriers for situation awareness recovery described above, drivers might have to prioritise certain visual information over others to perform a transition of control (Goodrich & Boer, 2003). This arbitrary information selection may increase variance in drivers' response to transitions of control and ultimately compromise drivers' safety. Louw et al. (2016) present empirical evidence to support such an idea by showing in a driving simulator experiment that drivers presented different outcomes to a safety-critical transition of control based on how early and continuously they gaze towards the road centre. According to the authors, the drivers who avoided a forward collision had an early and constant stream of fixations to the road centre. On the other hand, the drivers who crashed in the same scenario had a lower average fixation percentage to the road centre during the early stages of the transition process, with a sharp increase in the attendance to that area after ≈3 seconds. Their result suggests that drivers who could spot the hazard early had time to look for potential solutions for the situation at hand, indicating a higher probability of avoiding the accidents. However, their study focused the analysis on a statistical comparison between the groups of gaze behaviour based on the take-over outcome. Their results provide no further explanation about how this information was used in the take-over process or if other elements of drivers' gaze behaviour are also responsible for a safer transition of control. It is not clear if their pattern of visual information acquisition affected how quickly drivers react to a take-over, nor how valuable specific information sources are for the process of critical take-over.

As pointed out in our previous study (Gonçalves et al., 2019.a), evidence accumulation models (EAMs) may be a possible way to address the gaps in the literature presented above. EAMs are decision-making models capable of quantifying psychometrical variables responsible for the decision process. EAMs work under the assumption that evidence that supports an individual decision is accumulated over time until it reaches a threshold that triggers the human response (Ratcliff et al., 2016). This approach is not only capable of representing and quantifying elements that may interfere in the decision-making process but also integrate gaze pattern data from experimental datasets to evaluate how the visual attendance to some aspects of the environment may affect the action time and choice selection of an individual in a risky decision-making process. Gold & Shadlen (2002) suggested that more valuable information sources, once sampled, would lead to a faster accumulation of evidence leading to quicker reaction times. Empirical evidence can be found in the literature to support such assumptions, as in Usher & McClelland (2001), who developed a leaky accumulator model capable of accounting for the value of each information provided to the decision-maker to control their rate of evidence accumuation. Smith (1995) have demonstrated that different visual information presented to the decision-maker (varying noise and information coherence) affected their reaction time in simple decisions. Similarly, Krajbich et al. (2011, 2012) successfully used gaze fixation data in evidence accumulation models to estimate shop buyers' decision-making time and biases towards the purchase of certain supermarket products in a multiple-choice selection process.

Despite the EAMs' evident capability of depicting the decision-making process, when using gaze as a variable to control the drift rate, the models presented previously were not designed to the context of a transition of control. Most of the models cited above (Gold & Shadlen, 2002; Usher & McClelland, 2001; Ratcliff et al., 2016) were built based on abstract laboratory tasks, with no direct correlation to a real-world human task. This issue may compromise the direct application of such models on an applied scenario, such as modelling human responses to safety-critical transitions of control. A wrong application of models could lead to biases in the interpretation and unreliable results (Dullith et al., 2019). It is not clear from the state of the art of the literature on this field whether and how gaze data can be used to explain drivers' decision time and response to a collision-avoidance scenario, following a transition of control from level 3 automation.

7.2.3 Current Study

To address the literature gap presented in the previous section, the study reported in this document developed one EAM tailored to the specific scenario of safety-critical transitions of control from conditional automation, in order to understand how different information sources and gaze behaviour strategies could be linked with faster transitions of control and crash avoidance in such scenarios. The model developed was used to fit data from the EU-funded AdaptiVe project (Grant Agreement No. 610428) as a post-hoc analysis of an experimental dataset. The research questions proposed for this study were:

1. Can an EAM of which the evidence accumulation rate is determined by visual attention explain takeover response times in the decision-making process of a safety-critical transition of control?

2. Are there any differences between different information sources in how much they contribute to the evidence accumulation ratio in a decision-making process of a safety-critical transition of control?

3. If so, how much each visual information source contributes to the evidence accumulation process once sampled?

It was hypothesised that drivers' gaze could be used to determine drivers' response times during safety-critical transitions of control. The initial assumption was that early attendance to the road centre would be the best predictor of a fast decision-making process, leading to higher probabilities of crash avoidance (as suggested by the findings from Louw et al., 2016).

7.3 Method

7.3.1 Model description

Due to the nature of safety-critical transitions of control, the model described in this paper was based on the conceptual approach reported in Gonçalves et al. (2019.a), adapting the model developed by Krajbich et al. (2011, 2012) for the specific scenario of this study. We opted to adopt a single-alternative choice model, where every possible collision-avoidance manoeuvre (e.g. brake, brake, and steer, steer only) of the driver is considered to be the same "reaction" choice selection, and the crash outcome is considered to be a no choice selection. As in Krajbich et al. (2011, 2012), the slope of the evidence accumulation process is dependent on the location of drivers' gaze at the moment in time the evidence is accumulated, corresponding to our assumption that different information sources (or Areas of Interest, AoI) may be more informative towards the decision than others. The evidence value starts at 0 for each trial, then increases over time in a Markov Gaussian field process until it reaches a value of 1 (threshold, a) when the choice is made. The speed of each trial's decision-making time (DMT) is then dependent on drivers' gaze pattern plus a white noise inherent to the evidence accumulation process.

The main difference between the model proposed here and the one developed by Krajbich et al. (2011, 2012) is that their model describes a multiple-choice scenario, where there is competing information, and the evidence accumulation fluctuates between 1 (choice a) and -1 (choice b). In our model, all the information sources collaborate in different magnitudes for the decision to takeover control, in a consistently positive accumulation process (as suggested in Gonçalves et al., 2019.a), as in the formula (see Figure 7.1 for a graphical representation):

1. $E_t = E_{t-1} + d \cdot v_{aoi_t} + \varepsilon_t$
2. $E_{dmt} = a = 1$

Where E_t is the amount of evidence accumulated in a given time (t). v is a set of parameters ranging from 0 to 1 representing the value of the information source (AoI) that speeds or slows down the evidence accumulation process. d is a parameter scaling the v values to an evidence rate in the accumulator's units of evidence. a is the threshold for the decision (fixed as 1, following previous literature recommendations, Krajbich et al. 2011, 2012). ε_t is the white noise for the accumulation process, generated from a gaussian distribution with mean 0 and standard deviation $d \cdot \mu$.

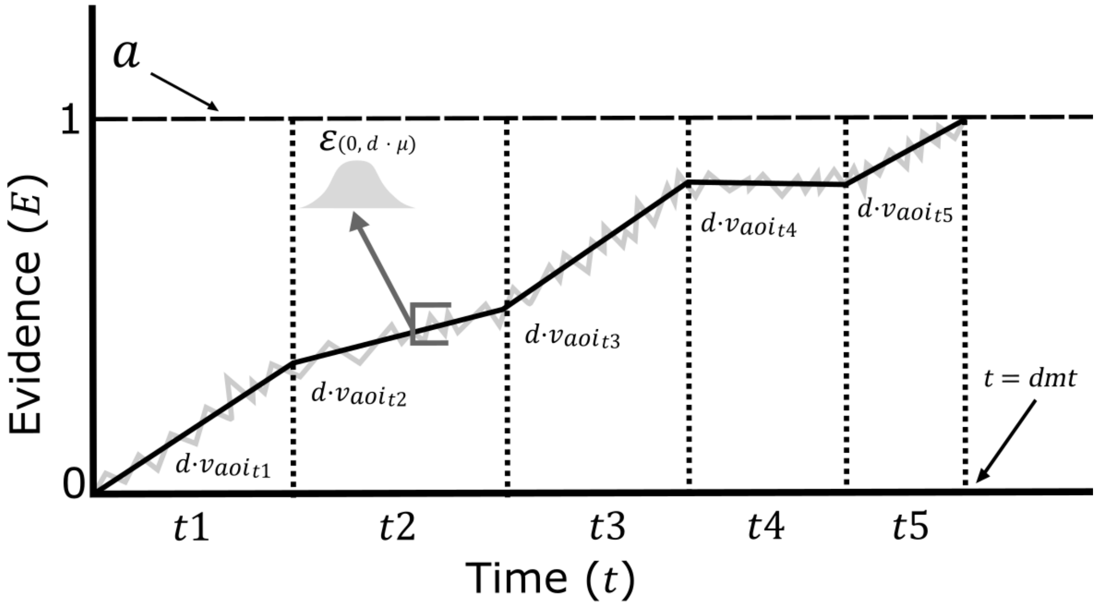


Figure 7.1 Schematic representation of the developed EAM

The black line represents the drift rate, controlled by v_{aoi_t}, while the grey line represents the real accumulation process, which is affected by noise, coming from the gaussian distribution ε.

The iteration of the model described in this paper follows the assumptions and abstractions described below: 1) It is assumed that the evidence accumulation rate stays the same for each AoI throughout the trial. 2) As the model calculates DMT based on the time collected from the gaze data, this approach assumes that evidence is being accumulated constantly throughout the decision process, and Ignores that saccadic movement or non-fixation gaze could not represent the actual acquisition of information (as suggested by Posner, 1980). 3) For simplicity, this model assumes that there are no additional response delays beyond the evidence accumulation time, i.e., the “non-decision time” in the model is zero.”

7.3.2 Experimental dataset

The dataset used for the model fitting was part of the AdaptiVe Project, collected by the University of Leeds. The dataset was initially designed to another study already published (see Louw et al., 2016, 2017, 2018) which aimed to understand how drivers acquire visual information to transition control from vehicle automation, varying the level of drivers’ engagement with the driving loop (as defined by Merat et al., 2019) and the criticality of the scenario. The similarity between the original study’s goal and the research questions proposed in this paper allowed us to use the same experiment design for a *post-hoc* analysis, complementing the original studies' findings to which the experiment was designed.

75 Participants (45.3% female) were aged between 21-69 years were recruited to participate in the study in the University of Leeds Driving Simulator. All participants were usual drivers (driving at least twice per week), with a mean annual mileage of 8290, and at least three years of driving license. All participants had normal or corrected to normal vision.

7.3.3 Experimental design and scenario

The experiment was composed of six automated car-following events, in a highway scenario, where drivers needed to take over control from the automation due to a system limitation. A 5x2 repeated measures design was used. As a between-subject factor, the experiment design manipulated drivers’ engagement with the loop (called OOTL manipulations; Louw et al., 2016), by using a fog, occluding totally or partially their field of view, and the presence of a secondary task, in these combinations: 1) no fog; 2) light fog; 3) heavy fog; 4) heavy fog + quiz; 5) no fog + n-back. As a within-participant factor, the criticality of the scenario was controlled by the presence of a decelerating lead vehicle in two of the events (events 2 and 6), and a failure/delayed transition of control in such cases would lead to a crash accident.

Since the model proposed by the current study was designed only to analyse driver's decision-making process during a safety-critical transition of control from a conditionally-automated vehicles, part of the data from the original dataset was removed. According to SAE's definition (SAE, 2021) conditional automation allows drivers to deviate their attention (visual and cognitive) away from the driving task, until a transition of control is requested. For this reason, only trials that belonged to the heavy fog and heavy fog + quiz conditions were selected from this dataset (30 participants), as they were the only two conditions which impeded the driver to sample information about the road environment, simulating a L3 automation distracted driver. Also, only the safety-critical events (trials) were used for this the model fitting (2 trials per participant). One participant had to be removed due to a technical failure on the steering wheel, and three others due to poor eye tracking gaze quality. Since our model only aimed to account for action time, we removed all trials that resulted in a crash (suggesting that no action was taken), resulting in a final sample size of 31 trials. To account for the crash trials, a separated logistic regression analysis was performed, aiming to identify which factors of the drivers' gaze could be related to their lack of reaction.

For both conditions used in this specific analysis (heavy fog and heavy fog + quiz), a heavy fog occluding participants' field of view appeared as soon as they turned on the automation, making it impossible for them to sample information on the road environment. For the heavy fog + quiz condition, participants also had to play a quiz game for as long as the automation was engaged. The critical scenarios were characterised by a sudden brake of a lead vehicle, which decelerated at a rate of 5 m/s^2, with a 3s time-to-collision (TTC). At the moment the lead vehicle starts braking, the heavy fog quickly disappears, allowing the driver to see the brake lights and the hazard in front. Also, an uncertainty alert is triggered on the human-machine interface of the automated system (HMI), located in the instrument cluster of the vehicle, at the same time the fog was resumed, alerting the participants to the potential danger (as described in Figure 7.2). There were no other vehicles or obstacles in the side lanes during the safety-critical events. For a more detailed description of the experimental design, see Louw et al. (2016).

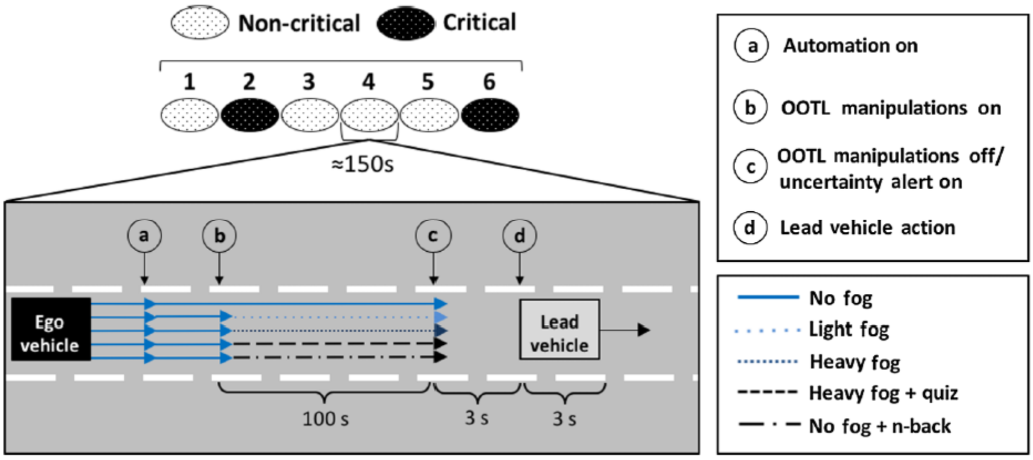


Figure 7.2 Schematic representation of each discrete event in the experimental drive. A–D represent various phases of the drive (Source: Louw et al., 2016)

7.3.4 Research variables

The main variables used from the experimental dataset for the fitting and validation of the model were drivers' decision-making time (DMT) and their total gaze distribution among different areas of interest (AoIs). For this analysis, DMT was calculated as the time between the end of the OOTL manipulations (heavy fog) until the time drivers engaged with the take-over process. Drivers' engagement with the takeover process was defined as the first non-negligible evasive action performed by the driver in the scenario. In the experimental scenario's context, the non-neglibible evasive actions available to the driver were either braking, steering, or a combination of both. The values for the trials' DMT were extracted from the study reported in Louw et al. (2018), which observed each trial individually, and the point of drivers engagement with the takeover process (DMT) was manually annotated according to the criterion described above. The extracted DMT acted as the ground truth to check the model's goodness of fit through Monte Carlo simulations using different model parameters. The DMT was calculated in frames at a ratio of 60Hz, to match the values from the eye-tracking data.

Drivers' eye gaze distribution among different AoIs was extracted from the V.4.5 Seeing Machines faceLAB eye tracker system installed in the experimental setup, recording drivers' gaze coordinates at a rate of 60Hz. The drivers' field of view was divided into five main AoIs, in a way that for every time-step of the eye tracker's gaze capturing, it was recorded which information source drivers were looking at. The division of AoIs followed the process reported by Carsten et al. (2012; see Figure 7.3 for a graphical representation of the AoI division).

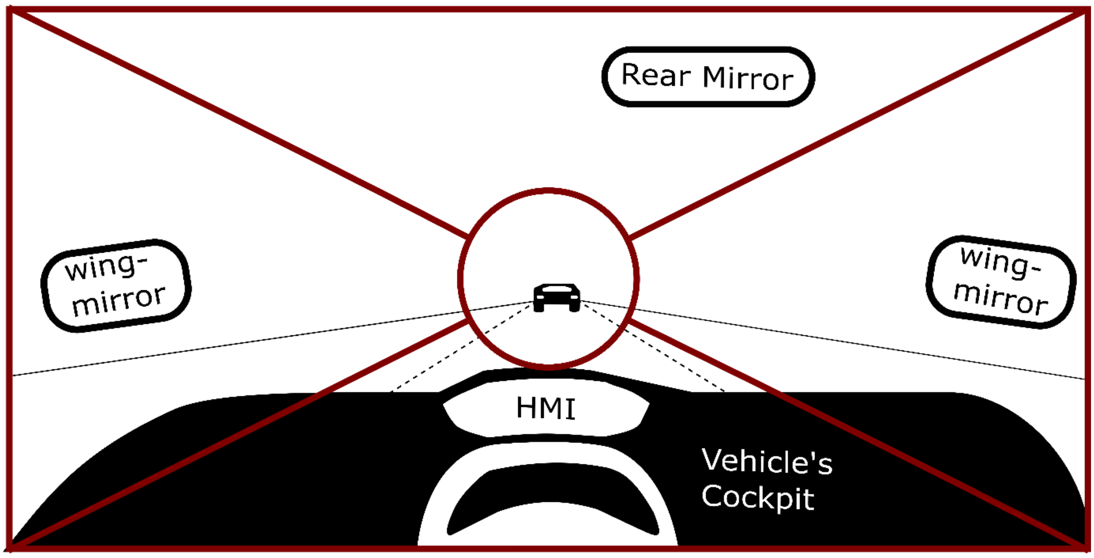


Figure 7.3 Schematic representation of the areas of interest. Based on Carsten et al. (2012)

Each cross-section of the figure separated by the red lines represent one of the AoIs used in this study. The centre is represented by the circular area where the picture of a lead vehicle is located. The left and right AoIs are represented by the area where the wing miirors are located. The top AoI is represented by the area where the rear mirror is located. The bottom AoI is represented by the area where the HMI and the vehicle's cockpit are located.

The first AoI defined in this process was the central region (called "Centre" throughout this document), which contained drivers' view of the road ahead and the lead vehicle. The centre region was calculated as a 6° circular area located in the mode of each participant's gaze fixations (see Victor, 2005) during the initial manual section of each drive (before the fog covered their field of view). Fixations were calculated as the participant's gaze's permanence in a 1° radial area for at least 150 ms, consistent with publications on time-based fixation detection algorithms (Salvucci & Goldberg, 2000). The other four areas were defined as equally distributed diagonal sections of the drivers' field of view, using the road centre as a reference. The top AoI (Top) contained all the information about the far road and drivers' rear-view mirror. Both the right-side (Right) and left-side (Left) AoIs contained visual information about their respective side-lanes, wing-mirrors as well as drivers' possible shoulder checks. The bottom AoI (Bottom) contained the visual information from the close elements in the road ahead and the information on the vehicle's instrument cluster, such as the speedometer and the automated system's HMI. As eye-tracking data is prone to noise and capture errors, all the missing data gaps smaller than 0.5s were interpolated with the expected gaze location based on the adjacent data stream.

7.3.5 Fitting and simulations

As presented in the Model description section, the models' equation was composed of 7 estimated and one fixed parameter. The decision threshold parameter a was fixed at 1, and estimated model parameters and their given range were d (0.0001 – 0.1), v_{aoI} (0 – 1) for the 5 AoIs, and μ (0-1). The parameters' values were estimated through a random search algorithm, which tested the goodness of fit for different combinations of parameter values using Monte Carlo simulations.

To account for the differences in each trial's gaze behaviour pattern, and also to account for the high dimensional search space of the parameters, we made the simplified assumption that all trials could be described probabilistically by the same model parameterisation. Based on that assumption, the fitting of each combination of model parameter was calculated separately for each trial (as in Svärd et al., 2020), using the experiment participant’s gaze data to define the AoI location during the simulation for each point in time. In this process, each time step (t) of any given simulation (measured in frames on a 60 Hz rate), the real trial's gaze location at the time t was used as a reference point for the AoI location during the simulation (replicating exactly the real experimental trial's gaze behaviour). This AoI location reference then fed the accumulator model, using the equation $E_t = E_{t-1} + d \cdot v_{aoi_t} + \varepsilon_t$, until the evidence value E reached 1, ending the simulation, returning the DMT = $t_{E=1}$. Since this evidence accumulation is a probabilistic process, even a perfect model would return responses both faster and slower than the observed ones. In the latter case, the model needs AoI input to drive it also after the observed DMT. One approach could have been to continue using the actual observed AoIs from the experiment, but since the AoIs after the observed DMT related to the driver’s performance of an avoidance response, we instead opted for creating artificial gaze data, closely replicating the statistical properties of the observed gaze data during the pre-DMT time; see the next section for full details. The model was coded in the Python 3.9 environment, using the StatsPy, and SciPy tools (Python Software Foundation, 2021).

7.3.6 Monte Carlo simulations of eye-tracking data

In an extensive literature review on the topic of gaze behaviour and visual attention distribution modelling, Borji & Itti (2013) reported several successful attempts and strategies utilised to depict and replicate the overall pattern of human eye movements, based on the observation of real human behaviour to a same given scenario. Boccignone & Ferraro (2004/2011) demonstrated that random visual information sampling behaves in a Levy Flight pattern (Checkin et al., 2004), where the duration of gaze on each clustered location follows an exponential distribution. The transition to the next cluster follows a gaussian Markov field (see Liu & Salvucci, 2001 and Gonçalves et al., 2019.b for successful applications of Markov chains to describe gaze transitions). Krajbich et al. (2011, 2012) also used a similar process to generate the simulations for their drift-diffusion models.

Based on the concepts presented above, we developed one algorithm that extracted parameters from the eye-tracking dataset and simulated a stream of data points of any given length with similar gaze distribution density among AoIs as in the real gaze data. The simulation started with the virtual participant looking to a given AoI *a* (from the 5 AoIs previously defined). Every time a simulated participant gazed one AoI *a*, the duration of the simulated gaze in *a* was randomly assigned following an exponential distribution with a given λ_a. Once the simulated driver reached the randomised limit of gaze duration, their gaze location moved to another AoI *b*, where the probability of the transition *a*→*b* followed a binomial distribution defined *p(b*|*a)*. Considering this process, a total of 5 λ_a (one for each AoI) and 20 *p(b*|*a)* (one for every combination of *a* and *b*) were estimated for the Monte Carlo simulations, based on the maximum likelihood estimators (MLE) extracted from the experimental.

The Markov Chain gaze transition probabilities $p\ (b|a)$ were based on the sample mean probability of every possible transition *a* → *b* across AoIs. It is assumed that every transition a→b followed *a* multi-dependent binomial distribution, where: $\sum_{b=1}^{b\neq a} p(b|a) = 1$. The λ_a values for the exponential distributions which generated the time permanence of the gaze in a given AoI were calculated as 1/sample mean gaze duration for each AoI.

7.3.7 Random search and parameter selection process

A random search is an algorithm that receives as entry values the range in which the parameters to be estimated can vary and iteratively tests different combinations of parameter values within the given range and checks how well each combination can generate simulation outputs that fit the real data (Bergstra & Bengio, 2012). This process is repeated a given number of times, and the combination of parameter values that returns simulations with the best goodness of fit is selected.

The algorithm developed for this study tested 100,000 possible combinations of parameter values for the evidence accumulation model, drawn at random from uniform distributions over the parameter ranges. The metric used to evaluate the goodness of fit was the log-likelihood values of the model output. The log-likelihood was calculated using the following process:

1. For each experimental trial (i) and set of randomised parameters ($\mathbb{P}$), a total of 10,000 Monte Carlo simulations were generated, and the resulting numerical distribution of DMT for the trial (denoted as DMT^{sim}) was stored.
2. A histogram of the simulated $DMT^{sim}|\mathbb{P}, i$ was made, and the model-predicted probability of a random datapoint to fall in each bin was calculated ($p\left(DMT^{sim} \in bin \middle| \mathbb{P}, i\right)$). The width of the bins for the histogram was set to 0.2s to be consistent with previous similar literature (Krajbich et al., 2011, 2012) and account for the precision needed on a collision-avoidance scenario.
3. The log-likelihood of the model for a given trial (i) and parameter set ($\mathbb{P}$) was calculated as $\log \ell_{\mathbb{P},i} = \log(p\left(DMT^{sim} \in bin \ni DMT^{real} \middle| \mathbb{P}, i\right))$, where DMT^{real} is the value of the real DMT observed on the referent experimental trial (i).
4. The final model's log-likelihood value for a given parameter set ($\mathbb{P}$) was calculated as the sum of the log-likelihood of the fitted models for every trial (i), as in the formula $\log \mathcal{L}_{\mathbb{P}} = \sum_{i=1}^{N} \log \ell_{\mathbb{P},i}$.

7.4 Results

The final output of the 100,000 iterations of the search process yielded a set of parameter values that generated a log-likelihood of -78.854. The constant parameter values that were used to generate the simulation output described above were d = 0.014 and μ = 0.536. The dynamic values for v_{AoI} can be seen in Figure 7.4, while Figure 7.5 shows a scatterplot of the combination of different parameter values, and their respective fitting values.

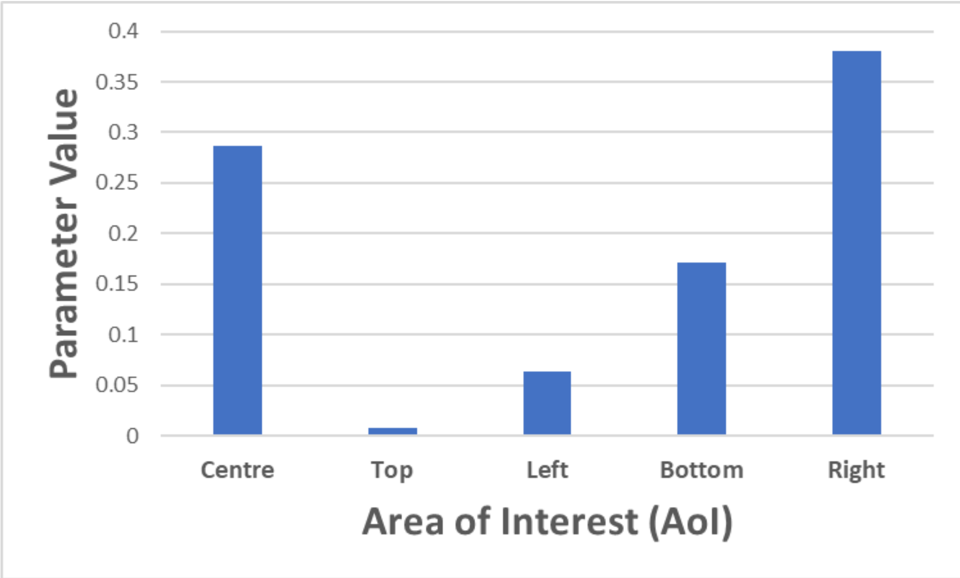


Figure 7.4 Parameter values for each AoI

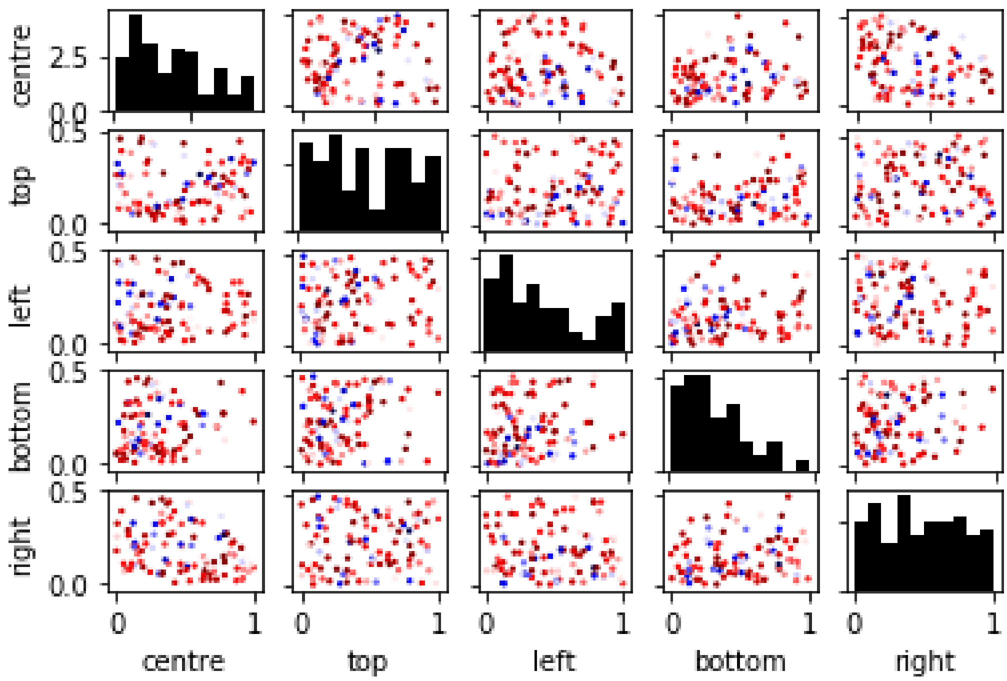


Figure 7.5 Scatter plot of parameter sets for model fitting

> Each axis represents the values for each of the model parameters, while the colours (ranging from red to blue) represent goodness of fit of the parameter set, where blue dots represents better model fits.

To test whether or not the addition of gaze behaviour data can be used to better explain drivers' DMT on transitions of control from conditional automation, followed by a forward-collision avoidance scenario, the performance of the model presented above (referred to in this paper as "gaze-based DDM") was compared to a standard single-alternative drift-diffusion model (Ratcliff et al., 2016), which assumes that evidence accumulation rate is independent of visual attention. According to Vandekerckhove & Tuerlinckx (2007), this type of drift diffusion model can be built based on 3 main parameters: 1) μ accounting for the mean of the gaussian function that defines the evidence accumulation process,2) s accounting for the standard deviation of the same gaussian function and 3) ξ as the mean for another gaussian distribution with fixed standard deviation of 0.1, which served as a factor to accounting for the across trial variability, altering the values μ for each simulated individual. The parameter selection and goodness of fit calculation conducted for this second model (nominated in this paper as "standard DDM") followed the same procedures used for our gaze-based DDM (described in sections 7.3.1 and 7.3.5). The performances of the models were compared using the Akaike Information Criterion, corrected for a small sample size of 31 trials (AICc), which evaluated the balance of their goodness of fit, in relation to their model complexity, in terms of the number of fitted parameters (Hurvich and Tsai, 1989; Sugiura, 1978). The AICc relative likelihood was used as the statistical criterion for model evaluation (Burnham & Anderson, 2004), under the null hypothesis that both models have equal probabilities of minimising information loss. Table 7-1 presents the results of the AICc tests and Figure 7.6 shows a visual representation of the comparison between the simulation outputs for both models and the real observed DMTs for each trial of the dataset.

Table 7-1 AICc values for comparison between models

Model	N	K	AICc	log£	ΔAICc	Avg. Error	Relative £
Gaze-based DDM	31	7	164.482	-78.854	0	0.497s	3.024e-05
Standard DDM	31	3	185.295	-91.519	20.813	0.914s	

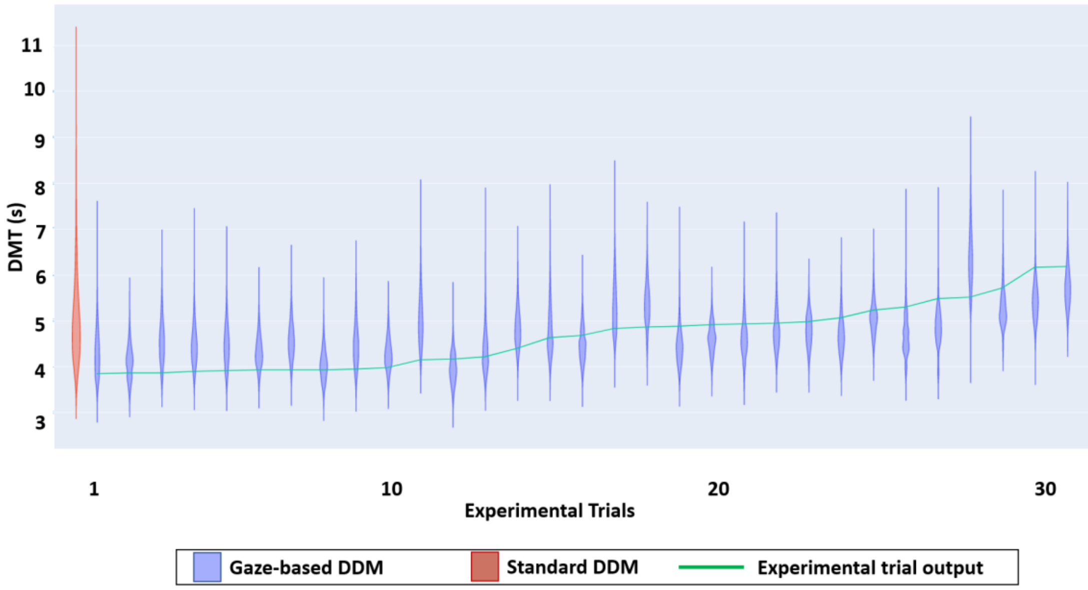


Figure 7.6 Graphical representation of both model's simulation output per experimental trial, sorted by observed DMT

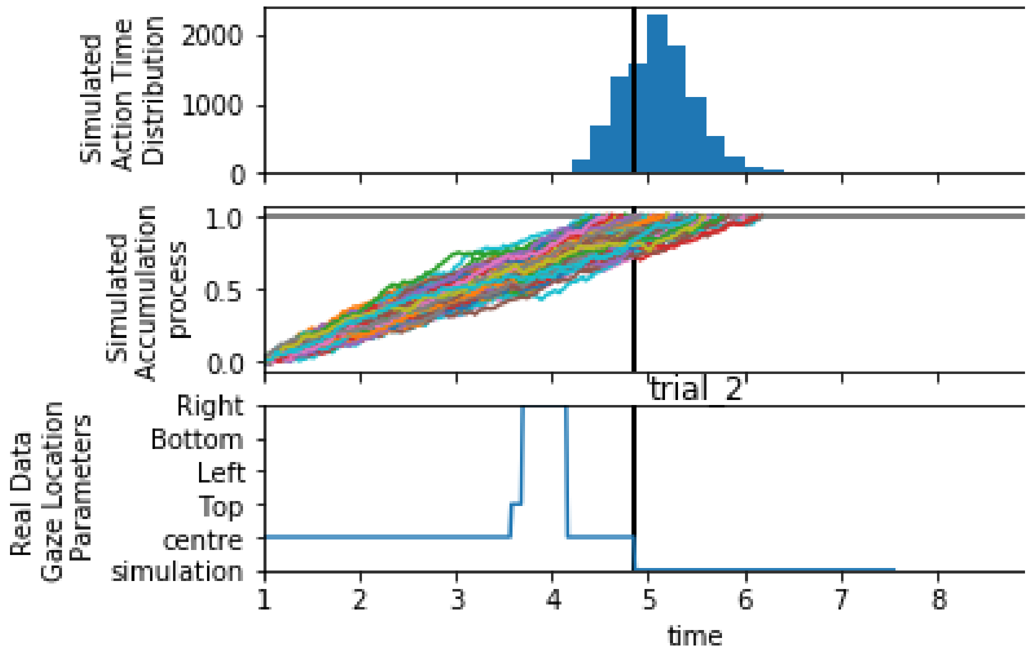
The violin plots represent the distribution of simulated DMTs for each trial. The green line represents the real DMT for the experimental trial. As the Standard DDM does not account for any variation across trials, only one violin was plotted as the reference for the whole dataset.

The results of the relative likelihood test, presented above, showed that significant differences exist between both models. Further comparisons between the respective models' fittings suggest that the inclusion of gaze data as a parameter in a drift-diffusion model increases its performance, as the gaze-based DDM had significantly lower AICc values. The most noticeable advantage of the gaze-based DDM is the reduction on the output's average prediction error (0.417s more accurate than the standard DDM). One possible explanation for this reduced prediction error, as can be seen in Figure 7.6, is that the way for the standard DDM to account to the across trial variability was to increase the noise in the accumulation process, resulting in a broader distribution for the simulation values, that can cover for the whole range of real DMT values of each trial. On the other hand, the gaze-based DDM was able to adapt the probability distribution of the simulated DMTs for each trial, suggesting that it was able to explain specific nuances of what constitutes drivers' decision-making process and reduced potential outliers, generated from the gaussian noise function.

7.4.1 Trials with observed response near model distribution mode

69% (21 trials) of all model responses had an individual log-likelihood fitting greater than -2.5, which could be considered an accurate prediction of the scenario (the prediction error for over 50% of the Monte Carlo simulations were within ± 0.4s of the real response in the experimental trial). Figure 7.7 shows the model response plots for two of these trials (illustrating a fast (a) and a slow (b) trial case), demonstrating the evidence accumulation process and the simulated DMT distribution.

a



b

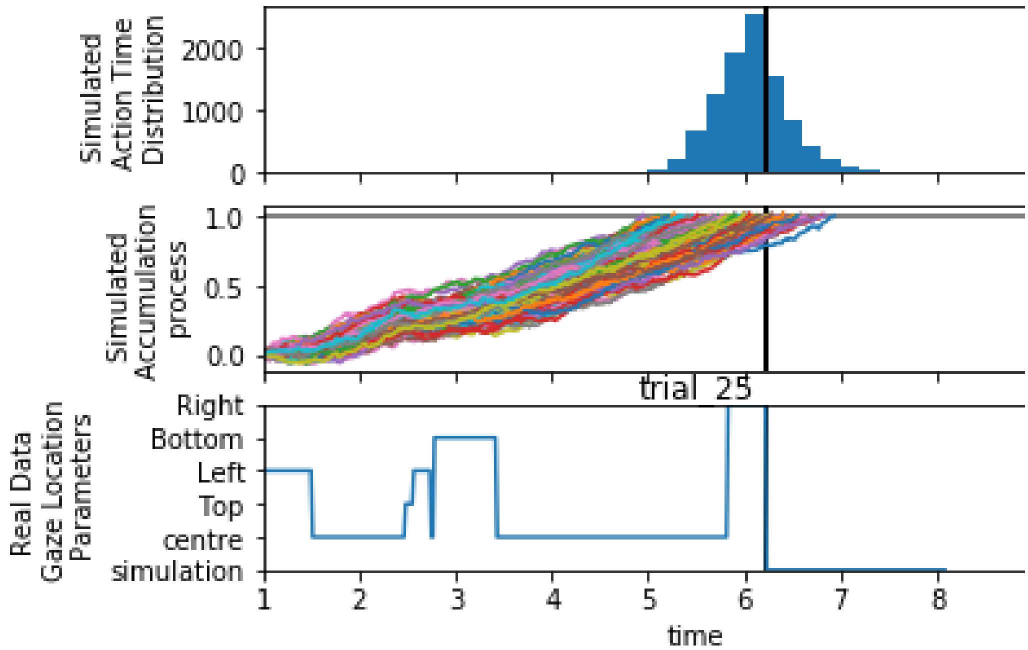


Figure 7.7 Graphical representation of the model output

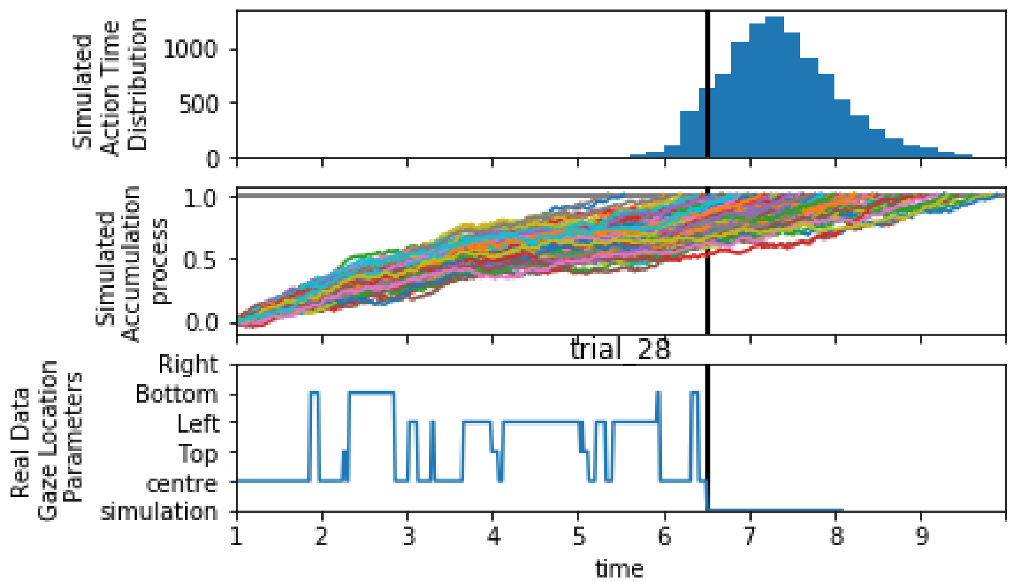
> Figure a shows an example of a fast reaction and b a slower case among the experimental trial. For each figure, the first subplot shows a histogram of DMT distribution for 10,000 simulations; the second subplot shows the graphical representation of the evidence accumulation process for the respective simulations, and the third subplot shows the trials' gaze behaviour, used as a parameter for the evidence accumulation. The vertical black line in the subplots represents the DMT of the real experimental trial.

By comparing Figures 7.7.a and 7.7.b, a reduction can be seen in the drift rate of the evidence accumulation process for the simulations in 7.7.b. By looking at the trial's gaze distribution, it is noticeable that this reduction occurred during the times when the gaze location was falling on AoIs with low importance values in the model parameters (e.g. left and top, between 2.5-3.5 s), explaining the higher average DMT, when compared to the simulations in 7.7.a.

7.4.2 Trials with observed response in model distribution tails

Across the 31 trials, there were a total of 10 (31%) cases that where the real trial's DMT was located near the model distribution tail (log-likelihood below -3, indicating that the predicted DMT values for more than 50% of the simulations for the trial is higher than ± 0.4s). The distribution between positive and negative average prediction errors across the 10 cases was consistent (4 negative, 6 positive). Figure 7.8 shows the model response plots for two trials, which were included in this group (illustrating a positive (a) and a negative (b) average prediction error for the trial case).

a



b

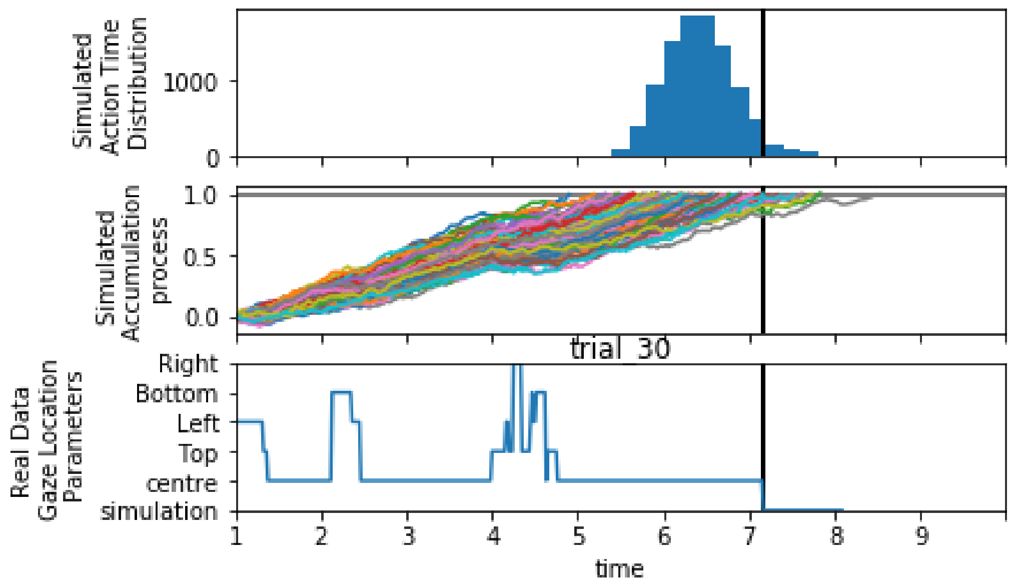


Figure 7.8 Graphical representation of the model output

For each figure, the first subplot shows a histogram of DMT distribution for 10,000 simulations; the second subplot shows the graphical representation of the evidence accumulation process for the respective simulations, and the third subplot shows the trials' gaze behaviour, used as a parameter for the evidence accumulation. The vertical black line in the subplots represents the DMT of the real experimental trial.

To look for potential bias and consistent errors caused by how long it took for the trials to takeover, linear regressions between the trials' DMT and the model's absolute prediction error were made (Figure 7.9). Results showed no significant correlation between those two variables [F$(1, 31) = 1.364$, p=.253, r^2=.046], suggesting that the model's prediction error distribution was consistent across each trial's DMT.

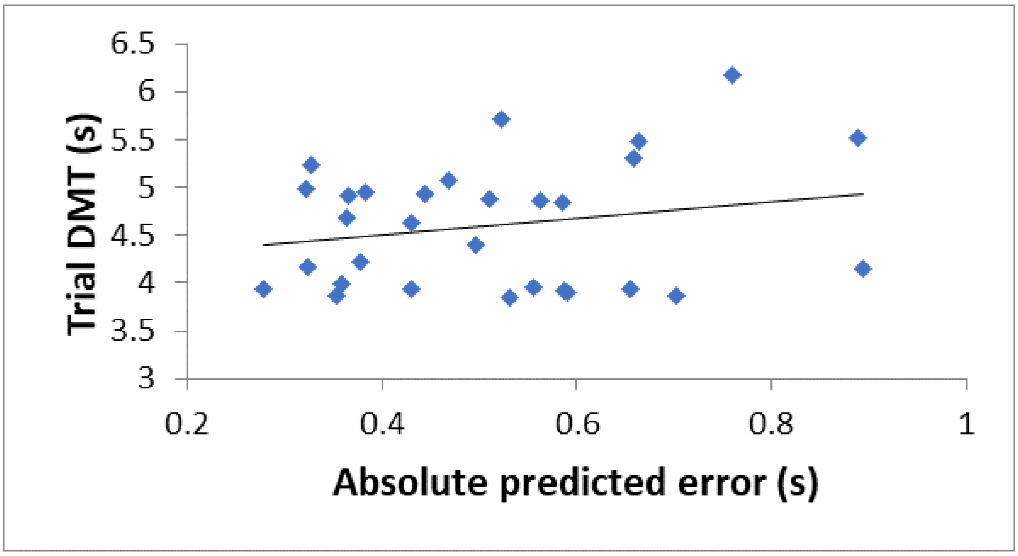


Figure 7.9 Linear regression between trial's DMT and the model's absolute predicted error

7.4.3 DMT simulations for the crash trials

To account for the trials that resulted into a crash, excluded from the parametrisation and fitting of the Gaze-based DDM, a series of 10,000 simulations were ran for each of the crash cases in the dataset, using the parameters selected above. Since the crash cases have no RT values, we could not directly to measure the accuracy of the model, and its capabilities to predict crash outcomes. To compensate for that issue, we used the distribution the simulated response times for the 31 non-crash scenarios and compared with the simulated response times from the dataset of the crash scenarios. Figure 7.10 shows a histogram with the distribution of the response times for the simulated response times, using the gaze data from the crash scenarios.

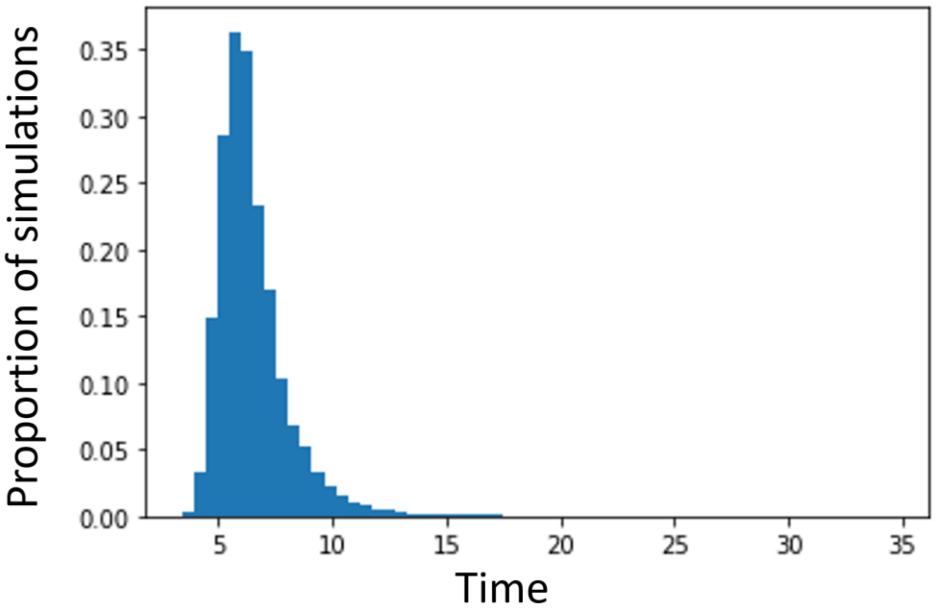


Figure 7.10 Histogram with the distribution of RTs for the crash scenarios

By observing the histogram above, we saw that the mean DMT for the simulation of the crash scenarios is 6.49 (SD = 1.59s), which is significantly higher than the experiment's scenario time-to-collision (5s), and is higher than the mean DMTs for the simulations based on drivers who avoided the crashes, in the experiment (M=4.97, SD = 1.15s). This result suggests that the model is able to spot slower reactions on driver's outcomes (that would arguably lead to a crash), using drivers' gaze behaviour patterns.

7.5 Discussion and conclusion

The model's output generated reasonably good fits to the real data, being able to predict drivers' DMT with an error margin below 0.5s for most cases. The AICc scores indicate that the drift-diffusion model, including drivers' gaze behaviour, does outperform a well-accepted model in decision-making literature (Ratcliff et al., 2016), which assumes that all AoIs provide equal amounts of information supporting the takeover decision . Another aspect that should be noted is that this model has not considered specific drivers' characteristics such as experience, age, gender, or aggressiveness profile to predict their DMT. This result suggests that drivers' decision-making to takeover control in a critical scenario may be explained with relative accuracy based on their visual information acquisition process (in consonance with the results reported by Svärd et al., 2020). This assumption is in line with studies on situation awareness recovery (Gartenberg et al., 2014), which suggests that the process of S.A. acquisition is composed mainly of a visual search task. The results are also aligned with previous studies on the field of collision avoidance and hazard perception (Crundall et al., 2003; Pradhan et al., 2009), which suggested that safe drivers are not the ones capable of quick reactions and reasonable steering wheel control, but rather the ones capable of efficiently scanning the environment to acquire the information they need to avoid potential threats.

By observing the parameter values for v_{aoi} in the 5 AoIs (Figure 7.4) it can be noted that two of them (centre and right) are notably higher than the others, suggesting that they are more informative, hence, providing faster evidence accumulation and thus faster reactions to the scenario. The lower value of the information on the bottom AoI (where the system HMI was located), in comparison to the centre (where the potential crash hazard was located), and the right (where the side mirror and potential collision-avoidance route was located) reinforces the idea that deviating drivers' vision away from the hazard to look to the inside of the vehicle (probably to check the system information or the uncertainty alert on the HMI) might be of little relevance for the take-over process, potentially even increasing risk in critical scenarios as noted in section 7.4.3. It must be noted that system information as well as a clear representation of the current status of the automation, and their respective alerts are undoubtedly crucial for the drivers' understanding of the system behaviour and their perceived usability of the product (see Beller, Heesen & Vollrath, 2013; Naujoks et al., 2018). However, this information may not be relevant for a critical transition of control, in which drivers must be focused on the hazard ahead and gain awareness of the environment.

The high value for v_{centre} was expected, given the results reported by Louw et al. (2016), where drivers who were able to avoid a crash outcome had an earlier and constant attendance to the road centre. It is evident that a good notion about an approaching obstacle ahead and its consequent looming effect might be relevant for their response to the scenario (Xue et al., 2018; Louw et al., 2018). However, the model output suggests that the right AoI is equally or more important for a quick DMT. Considering the experiment scenario, where there were no potential other obstacles on the side lanes, we can assume that drivers who observed the lateral lanes could quickly figure out how to perform a collision-avoidance manoeuvre, which is in line with the behaviour observed in the experimental data, since all drivers who could avoid the crash used a combination of brake and steer to the side lane. This interpretation suggests that it is not only important for the driver to detect early on the presence of the hazard ahead (as suggested by Louw et al., 2016), and its approaching speed to define their decision time budget (as suggested by Xue et al., 2018), but also to efficiently scan the conditions of the environment, in order to acquire relevant information about how this threat can be avoided.

Considering the trials which the real DMT was located near the tail of the simulation distribution, as could be seen in Figure 7.8.a, regardless of the low values associated to v_{left} and v_{bottom}, some drivers were capable of quickly reacting to the scenario by mainly focusing on those two areas. One possible explanation for these results is that there is not one only solution to a collision-avoidance situation. As the scenario provided a very diverse solution space, it is possible that some drivers adopted different strategies, reaching a reasonable solution, relying on different information. This assumption also explains the wide spread of possible good fit parameters found on Figure 7.5. As the model presented in this paper generalises overall weight values for the importance of the information in each AoI, considering the overall distribution of DMTs across all trials, it is not sensitive enough to capture potential differences in drivers' collision avoidance strategies, a limitation to be addressed in future research. Another possible explanation for the observed result can be associated by the simple fact that DMTs are probabilistic by nature. As every predictor model is a simplification of a complex phenomenon, it is expected that some cases will present a poorer fitting due to its inherent randomness. The output of the model reported in this paper is also limited by the scenario condition used for the parameter estimation process, as gaze behaviour/information value is entirely scenario-dependent (Borji & Itti, 2013). The value of information sources may change in different critical situations. New studies are necessary to confirm the results presented above, applying similar methods on different scenario conditions and with different information presented to the driver.

The contributions to this work for the state of the art of the field comes from a modelling perspective. The model can explain in a mechanistic way how visual information is used on the decision-making process of a transition of control. By assigning value for the different information sources on the process of evidence accumulation on a critical take-over, one can now understand how useful certain information is as a tool to prevent a critical situation. This can end up providing tools for future system designers, to highlight certain information on their systems, and designing the vehicles accordingly.

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8.
Discussion and conclusions

8.1 Research Outlook

The main objective of the research described in this thesis was to investigate how the degree of drivers' involvement in the decision-making and control loops of the driving task (as described by Merat et al., 2019), the kinematics of the scenario, and the information available in the road environment and the vehicle's Human Machine Interface (HMI) affect the way drivers distribute their visual attention during the take-over process from different levels of vehicle automation. The end goal of this investigation was to understand whether or not driver takeover performance could be predicted using gaze patterns, establishing if certain gaze behaviour patterns are more likely to yield safer transitions of control from automation.

The motivation for this research is based on the challenges related to drivers' situation awareness recovery (Gartenberg, 2014), and their visuo-motor coordination activities (Mole et al., 2019) during the take-over process, which sometimes exceeds users' information processing capacity (Endsley & Kiris, 1995, Goodrich & Boer, 2003), especially in time-critical situations. This research assumes that by understanding drivers' visual scanning patterns (Borji & Itti, 2013) during the transition process, it is possible to tailor the location and level of useful information from HMIs, to assist them with a safe and timely resumption of control.

This research had, as its theoretical basis, the concepts of situation awareness (Endsley, 1995), and situation awareness recovery (Gartenberg, 2014), aligned with the theories of risky decision-making (Edwards, 1954) and bounded rationality (Simon, 1972). The rationale behind this approach was to consider the process of transition of control from an automated vehicle as a risky decision-making process, where the decision-maker (driver) is under time pressure to respond to a take over request (TOR), and is, therefore, unlikely to be able to process all the information needed to make a fully rational decision. With that in mind, it can be assumed that drivers' decision process is inherently biased by the information they were able to acquire before a transition (Orquin & Loose, 2013), therefore, yielding different safety outcomes, based on the driving scenario and circumstances.

This research performed post-hoc analyses of drivers' gaze behaviour from the eye tracking data collected for four driving simulator experiments involving take-overs, which controlled:

1) drivers' involvement with the physical control loop of the task (Goncalves et al., 2020, Goncalves et al., 2019);

2) drivers' involvement with the decision-making cognitive loop of the driving task, as well as changes in the situation kinematics during the takeover process (Goncalves et al., 2022);

3) presence of supportive information on the vehicles' HMI (Goncalves et al., 2022)

4) a critical driving simulator scenario with drivers completely removed from the loop of the driving task, until the takeover request was triggered (Goncalves et al., under review).

In terms of the methodological approach, descriptive data from drivers' gaze behaviour was analysed as a time series, depicting gaze concentration in different areas of interest, while their attention shifts were characterised using Markov Chains (see Goncalves et al., 2019), estimating the probability for shifts of attention. To understand how drivers' visual information acquisition was used in their decision-making process, this research made use of machine learning regression methods (see Goncalves et al., 2022), as well as drift diffusion evidence accumulation models (see Gonçalves et al., 2019; Goncalves et al., under review), that considered the real-time gaze location of each individual trial as a mediator of their evidence accumulation rate, assuming that certain visual information would be more relevant for the decision-process than others.

The results provided knowledge about the impact of different takeover scenario specificities on the way drivers allocate their visual attention across the environment, during the transition of control from automation. The results also allowed the develop models to predict, with relative accuracy, drivers' safety outcome of a critical takeover, based on their gaze patterns. , suggesting that certain aspects of the drivers' gaze behaviour can be associated with a safer transition process. The next section outlines the the research questions posed in this research programme, and summarises the main results of this PhD, closing some of the gaps found in the literature.

8.2 Overview of the Research Questions

This PhD addressed the 2 following research questions, and its subquestions:

- How are the competing demands of visual information prioritised during drivers' transition of control from vehicle automation?
  - What is the effect of drivers' engagement in the motor control and cognitive loops of the driving task, on their visual attention allocation patterns during transitions of control from vehicle automation?
  - How does the type of information presented on the HMI of an automated system affect drivers' gaze behaviour during transitions of control from vehicle automation?
  - How does the scenario kinematics affect drivers' gaze behaviour during transitions of control from vehicle automation?
- How can the pattern of drivers' visual attention allocation be correlated with their decision to transition control from vehicle automation?
  - What is a safe gaze behaviour pattern for successful transitions of control?

8.2.1 How are the competing demands of visual information prioritised during drivers' transition of control from vehicle automation?

1. What is the effect of drivers' engagement in the motor control and cognitive loops of the driving task, on their visual attention allocation patterns during transitions of control from vehicle automation?

When it comes to drivers' engagement in the motor control loop, the study described in Chapter 2 provides evidence that drivers in an automated driving scenario, who are therefore, not involved in the motor control loop, have, a higher average gaze dispersion across the environment, when compared to a manual drive. These results were expected and are in line with those of Mars & Navarro (2012), Mackenzie & Harris (2015), and Louw & Merat (2017)

The study reported in Chapter 2 also found that any differences in gaze behaviour during automation, quickly converged as drivers' role changed from that of a passive observer to more of a controller, which in this case involved the potential need to intervene and perform an overtaking manoeuvre. Indeed, this study found that drivers' glance patterns were similar to those found in manual lane changing tasks (Tijerina et al., 2005).

This result supports the idea that top-down demands on strategic and tactical levels of driving (as defined by Michon, 1985) generally get priority for drivers' visual attention resources, therefore diminishing any potential effects caused by the lack of need for physically interacting with the driving task. This finding is in line with previous literature in this field (see Louw, 2017; Tivesten et al., 2015), which reports that differences in drivers' gaze patterns quickly disappear after automation is disengaged, as drivers engage in a visual search task of their surrounding environment, to recover situation awareness for safe resumption of vehicle control. Results also suggest that, even when in automation (at least in such driving simulator studies), drivers are well aware of what information to look for, triggering a discretionary gaze behaviour (Trick & Enns, 2009) towards specific (informative) locations, based on their previous experience, as a top-down modulation of attention (in line with the models described by Borji & Itti, 2013).

As a counterpoint to the evidence provided by Chapter 2, the study described in Chapter 3 showed that despite the gaze concentration pattern for drivers in different levels of engagement with the motor control loop being similar, the sequence of attention shifts across the different information sources were significantly different. The results presented in Chapter 3 showed that drivers who experienced an overtaking manoeuvre without physically interacting with the motor control aspect of the task (moving the steering wheel) presented a very erratic attention shift pattern, with a much higher frequency of saccadic movements across the different information sources (HMI, side mirrors, road ahead etc.), when compared to the condition where drivers needed to resume manual control of the driving task to change lane. This study also showed that those shifts of attention (as evidenced by gaze pattern), were not only erratic, but that drivers rapidly shifted their attention between two information sources, without fixating on the road centre. Considering our current understanding of visuomotor coordination (Land 1998, Wilkie & Wann, 2010), which defines guiding fixations as a fixation on the near field of view of the road centre, one can assume that drivers who were not engaged with the physical control of the driving task, were less likely to perform motor control-related gazes (i.e.

guiding fixations), even though they had a similar gaze concentration to the road centre as the drivers in the manual control condition . This assumption is in line with previous literature (Mckenzie & Harris, 2015; Mars & Navarro, 2012), which suggests that gaze concentration towards the road centre is not necessarily related to the locomotion of the vehicle, but rather for monitoring the headway of a lead vehicle, in order to initiate an overtaking manoeuvre. As a conclusion, one can assume that lower levels of drivers' engagement with the motor control loop of the driving task does not necessarily lead to an erratic gaze dispersion, but rather gives room for drivers to prioritise their attention towards strategic discretionary gaze patterns, using a top-down control of attention.

When it comes to drivers' engagement in the cognitive loop of the driving task, the study described in Chapter 4 (where part of the drivers needed to transition control from vehicle automation in SAE levels 2 and 3) showed that drivers who performed the experiment in SAE Level 3 automation (SAE, 2021), showed a higher dispersion in gaze pitch, when compared to drivers in Level 2 automation. The believed explanation for such a result was that, given that drivers in level 2 automation were required to monitor the environment during the automated drive, they started the takeover process with a better awareness about the road environment, therefore, requiring less effort during the process of situation awareness recovery. In other words, as drivers were looking towards the road scene, they were aware of the relative position of the surrounding vehicles, as well their relative speed, in relation to the potential hazards. Since those information are essential for their decision-making process when taking over control of the vehicle, it is fair to assume that drivers' needed to sample less additional information from the environment, as they received the takeover request. On top of that, the Markov chain analysis presented in Chapter 4 showed that drivers in level 3 automation had a much higher frequency of attention shifts across multiple sources of information (such as the instrument cluster, mirrors, road centre and the sides of the road). These erratic patterns of attention shifts and higher gaze dispersion are in line with the standard situation awareness recovery process, described by Gartenberg (2014). This relationship with the literature suggests that drivers with lower levels of situation awareness, despite presenting an overall similar gaze distribution over time, when compared with drivers more engaged in the cognitive loop of the driving task (acknowledging the findings from Louw, 2017), are required to acquire a larger volume of visual information. It is argued here that larger demands for visual attention may stress drivers' short-term memory (as suggested by

Endsley & Kiris, 1995), requiring them to refocus their attention on different sources of information, leading to potential risks to the transition process.

2. **How does the type of information presented on the HMI of an automated system affect drivers' gaze behaviour during transitions of control from vehicle automation?**

The study presented in Chapter 5 provided evidence that the more information provided on the HMI of an autonomous vehicle, the longer drivers spend looking at it, in the moments preceding a transition of control from vehicle automation (e.g. after receiving a takeover request). Based on literature on situation awareness, and situation awareness recovery (Endsley & Kiris, 1995; Gartenberg, 2014), one possible explanation for these data is based on attentional tunnelling (i.e. over focusing on a certain visual element/information due to limited information processing capabilities), due to the amount of extra visual information to be processed. Given the fact that drivers presented increased visual attention to the HMI of the vehicle whenever extra information was presented, and also its correlation with the decision-making time on the Chapter's regression analysis, one can suggest that drivers tend to rely on visual information provided by the system, actively assessing it, whenever available. On the other hand, the study in Chapter 5 also showed that the manipulations of visual information on the vehicle's HMI had no statistical effect on drivers' decision-making time, to resume control of the vehicle and perform a lane-change. At first glance, this result would go against studies by Naujoks et al. (2017), and Richardson et al. (2016), who suggest that active support from the vehicle's HMI may improve drivers' response times, as they are providing targeted, relevant information. In this study, results from the random forest regression model showed a good correlation between drivers' decision-making time, and the proportion of their glances towards the vehicle HMI, if this information was actively supporting the driver in their decision (e.g., presenting a green arrow on the HMI, suggesting it was safe to perform a lane change). This result supports the idea that HMI information was relevant to drivers' decision-making process, whenever sampled. It is then believed that the cause for the lack of improvement in drivers' decision-making time could have been caused by a secondary side effect of the experimental manipulation, not envisioned on the initial hypothesis. As pointed out by Ali et al. (2021), the presentation of additional information on the HMI of a vehicle does not mean that drivers will sample the new information instead of the road environment, but rather will add this as one extra element on their information scanning routine. Therefore, even if the information on the HMI was beneficial to the driver, the lack of effect on drivers' DMT may have been caused by the increase in visual information to be sampled. On the other hand, it is possible that additional HMI information may also present other benefits to the takeover process, not directly related to takeover time, such as reduction of stress, and increased trust. New studies are required to assess the subjective benefits of HMI manipulations to support the takeover process.

By observing differences in drivers' gaze concentration across the different information sources in the experimental design reported on Chapter 5, it was noted that drivers' proportion of visual attendance dedicated to the side mirrors was not affected by the information presented on the HMI of the vehicle. In other words, even when the system provided the same information as the road environment, drivers still looked at the mirrors, before performing a lane change, as they would in a fully manual drive (Salvucci, Liu & Boer, 2003). In fact, the only observed trade-off caused by the increased gaze concentration towards the HMI was a reduction of gazes to the road centre, which was already expected, since the drivers were not in active control of the vehicle (see Louw & Merat, 2017). A possible interpretation to a similar observed phenomenon was proposed by Ali et al. (2021), when affirmed that the presence of supportive information provided by connected vehicles may bring improvements on discretionary lane-change manoeuvres (in terms of perceived safety, and vehicle controllability), however not necessarily to the speed of the decision process. The authors' explanation was that drivers have not changed their visual scanning patterns to assess the vehicle's HMI, but rather added this element on their visual scanning routine for lane change, on top of the usual information previously assessed. Based on the findings above, it is believed that the results on Chapter 5 suggest that the supportive information on the HMI of an automated vehicle indeed supported the driver on their decision, however, it does not get priority in drivers' gaze behaviour patterns over the information provided by the road environment. Therefore, it is suggested that automated vehicle's HMI should be designed taking into account potential side effects caused by visual distraction (i.e., deviation of visual attention resources to less relevant information sources), and on the fact that it will not be the main source of information for drivers' decision, which will likely always be the road environment.

3. How does the scenario kinematics affect drivers’ gaze behaviour during transitions of control from vehicle automation?

The initial hypothesis for the study described in Chapter 4 was that drivers with lower levels of situation awareness (brought about by an non-driving-related task) would be more sensitive to bottom-up manipulations of visual attention, because they would not necessarily know where to focus their visual attention, after a takeover request, and fixating on any potential hazard ahead (a phenomenon called weapon focus in Chapman & Underwood, 1998). Evidence for weapon focus on safety-critical transitions of control could be found in Louw et al. (2016). The authors reported that drivers who have a delayed attendance to the road centre during a transition of control with a potential obstacle ahead (like the delay observed on drivers’ in L3 automation on the study in Chapter 4) presented a steady focus on the vehicle in front, as they were about to crash.

However, results from the study reported in Chapter 4 showed that drivers with low levels of situation awareness, whenever facing a potential hazard, presented a scattered gaze pattern, with a high index of gaze transitions between different information sources, such as the instruments’ cluster and the road centre. On the other hand, drivers with lower level of situation awareness that transitioned control without the presence of a potential hazard in front presented a steady index of fixations towards the road centre during the whole transition period. This result was the opposite of what was expected from the experimental data, as it is believed that the lack of bottom-up saliences of attention would lead to a higher gaze dispersion, triggered by an exploratory gaze routine (Trick & Enns, 2009). On the other hand, this finding is in line with the theories of Gartenberg (2014) and Endsley (2005), that suggests that the process of situation awareness recovery follows a memory for goals model (see Altmann & Trafton, 2002). In this line of thought, it is believed that the presence of potential hazards in drivers’ field of view, instead of attracting their gaze, as a bottom-up saliency, acted as a stimulus, triggering a more urgent, yet erratic discretionary scanning behaviour, so that drivers could accumulate as much information as possible, before transitioning control from vehicle automation. Regarding the cases with no potential hazard, since there was no threat during the transition process, drivers had no motivation to look for additional information, and continued looking to the road ahead, since they were about to resume control.

Complementing the findings above, the study described in Chapter 5 showed that higher traffic density, in cases of higher uncertainty, like a lane change scenario, may indeed attract drivers' gaze. The experiment results showed that during transitions of control followed by a lane change task, the closer the vehicles on the offside lane, the longer drivers tended to look at them. This result is in line with theories of Shaw (1986), suggesting that humans (in this case, drivers), tend to spend more time looking towards elements that may reduce the uncertainty on their decision-making. Since the task in hand on this experiment was a lane change, it is expected that drivers would spend longer times looking to the side mirrors, since it is the most relevant information source for a lane change task (Tijerina et al., 2005). This result is in line with the findings above, suggesting that the kinematics of the situation may not only act as a bottom-up saliency of attention, but also trigger discretionary gaze behaviour to relevant information sources, based on drivers' experience (as also suggested by Sullivan et al., 2012).

4. Final thoughts on the first main research question

Considering the arguments presented for the three previous minor research questions, it can be concluded that the main factor affecting drivers' gaze, in terms of a top-down structure of attention, is the task they are about to perform. The sections above showed that despite the other scenario conditions, drivers presented a similar gaze behaviour pattern for both transitions involving a lane change or forward-collision avoidance as the gaze patterns reported in the literature on similar scenarios (e.g. Tijerina et al., 2005). This conclusion advocates in favour of the fact that drivers will always act based on their previous experience with similar situations, triggering discretionary scanning routines, rather than changing their behaviour because they were not in active control of the driving task.

On the other hand, the studies in this thesis were able to confirm that the lack of drivers' engagement with the decision-making and control loops of the driving task may increase drivers' demands for information, and therefore disperse their gaze across the environment. The last thing to be observed is that, despite the undeniable value of HMI information, drivers will always rely on the road environment as their primary information source, whenever they need to prioritise their resources to access information.

8.2.2 How can the pattern of drivers' visual attention allocation be correlated with their decision to transition control from vehicle automation?

1. What is a safe gaze behaviour pattern for successful transitions of control?

Regarding whether certain gaze patterns can predict a safe transition of control from vehicle automation than others, the model described in Chapter 7 was able to explain with relative accuracy (under .5 s average error margin) the individual differences in decision-making time for a safety-critical transition of control, based on the way drivers distributed their gaze across the environment. This finding suggests that some gaze patterns observed during and before transition of automation are safer than others, which is in line with past literature in the hazard perception domain, for manual driving studies (Horswill & McKenna, 2002; Crundall & Underwood, 2010).

The best parametrisation of the model described above suggested that drivers were able to accumulate a significantly greater amount of evidence, when sampling information from the right side mirror, which therefore led to faster decision-making times. On the other hand, drivers who spent time looking towards the instrument cluster of the vehicle (either to the speedometer or the system's HMI) or to the left/rear-facing mirror presented a lower evidence accumulation rate. It is believed that drivers who quickly assessed the information about the environment, and the possible collision-avoidance manoeuvring options (such as checking if the offside lane was free, so they could steer out of the way and avoid the impend obstacle) were able to make a quick decision, yielding a higher probability of avoiding a crash. This result complements the findings from Louw et al.'s (2016) work, which suggested that drivers with an earlier visual attendance to the hazard in the forward view/road centre area, had a higher probability of performing a successful avoidance manoeuvre. The argument provided here is that it is not only important to quickly recognise the situation at hand, but also to manage a quick and targeted scan of the various solutions in the environment. In this scenario, that would be the possibility of entering the side lane, in order to avoid an impending collision with a lead vehicle.

There are many cases in the literature which suggest that increased dispersion of gaze away from the road centre during the transition process may be detrimental for the takeover process (e.g. Zeeb et al., 2016). However, the arguments provided in Chapter 7 go against this idea, and suggest that if well-directed (and top down), gaze dispersion may be one good indicator of effective situation awareness recovery, as well as signifying an efficient hazard perception strategy.

2. Final thoughts on the second main research question

The model described in Chapter 7 provided evidence to support the idea that drivers' gaze patterns can be used to better understand and predict their decision-making process during transitions of control from automation, when compared to generalist models, that generate their sample of response times from Monte Carlo simulations drawn from a Gaussian distribution (Ratcliff et al., 2016). The output of the model also provided support for the theoretical consideration presented in Chapter 6, suggesting that there is a strong relationship between the process of situation awareness recovery (Gartenberg, 2014) and the process of evidence accumulation, which are necessary for a decision (Ratcliff et al., 2016). This result complements the applicability of the theories suggested by Krajbich et al. (2012), and Orquim & Loose (2013), that gaze behaviour can be considered as a factor that biases a risky decision-making process, under the assumption that certain information, once sampled, provides a higher rate of evidence accumulation towards a particular decision. The contribution for the work present in Chapters 6 and 7 also provide further contribution to decision-making theory computational models, as they provide evidence that gaze-based evidence accumulation models can be directly applied on the context of transitions of control in vehicle automation, due to is above-mentioned relationship with the process of situation awareness recovery.

8.3 Methodological Considerations and Research Limitations

8.3.1 Considerations about the effects of long-term experience with vehicle automation on drivers' behaviour

A consistent result found across the studies was that drivers' gaze behaviour during transitions of control were generally similar to those seen for manual driving. This may be because vehicle automation is still a novelty for the majority of the population, and drivers' behaviour has not yet adapted to the changes likely imposed by this technology. In addition, most of the participants had limited or no previous experience with this kind of vehicle. Therefore, the results reported might have been influenced by drivers' lack of experience with automated vehicles. Previous research suggests that, in manual driving, automatised behaviour, based on habits, develops over the course of years (see Charlton & Starkey, 2011), that might change as they gain more experience with automated driving. Also, it is possible that issues related to trust (Lee & See, 2004) might also have affected drivers' interaction with system-related information, such that as drivers become more familiar with the behaviour of an automated vehicle, they change the way they access information during a transition process. In line with the arguments presented above, this research recommends studying how long-term interaction with automated driving affects drivers' gaze patterns.

8.3.2 Considerations about scenario design and attentional saliences

In Chapters 2-5, this thesis has discussed the effects of certain scenario manipulations on the way drivers distributed their visual attention across the environment. It is acknowledged that drivers' visual attention is based inherently on the information available to them in the driving environment (Hayhoe & Ballard, 2009; Borji & Itti, 2013). Therefore, it is likely that, arbitrary choices - such as the chosen HMI design of the vehicle's dashboards - might have affected how much drivers relied on certain information sources to recover situation awareness. Therefore, future studies should explore how different types visual of information from an HMI (e.g. heads up displays, or different HMI designs) affect drivers' gaze patterns during transitions of control. On the other hand, it is argued here that the bottom-up and top-down saliencies of attention were systematically manipulated to understand the overall impact of different situations on drivers' behaviour. Therefore, even though the output of this research is not able to define a general structure for drivers' attention selection during takeover, it is believed that the findings are transferable to the most situations where a transition of control is required.

Another consideration that must be noted is that for chapters 4 and 5 the manipulation of "level of automation" directly manipulated their visual attention selection strategies. In the experiments described on both chapters, L3 automation was emulated by the usage of an NDRT (arrows task), that prevented driers from sampling visual information on the road environment. Considering this case, it is possible that certain results may be biased, in terms of raw observation of attention selection and gaze distribution for drivers in L3 vehicles, as a manipulation of attention selection was forced into them. Therefore, the results should not be interpreted as a real representation of a driver in an L3 vehicle, but rather of how a completely unaware driver would react to a takeover situation. As a counterpoint, the evidence showed in these experiments depict an extreme case of an inattentive driver of an automated vehicle, which is likely to happen in higher levels of vehicle automation (see Carsten et al., 2012).

Regarding Chapters 6-7, the model described in this thesis showed that glances towards the side mirrors generated a significantly faster evidence accumulation process for drivers' decision-making than other information sources. This research acknowledges the fact that the value for certain information sources in a decision-making scenario is inherently dependent on the situation at hand. It is possible that if the side lanes were always occupied by other vehicles during the lane change, the value of information provided by the side mirrors might have been lower than that observed in the current study (described in Chapter 7). It is argued here that the fitting of the model was not intended to generalise the overall importance of all sources of information during a safety-critical transition of control, as it is a stochastic scenario by nature. Instead, the model fitting was developed as a proof of concept, to raise highlight the role and importance of different visual attention selection strategies, in drivers' decision-making process. The output of this research does to directly influence the design of safer products, but provides knowledge and tools that may be used, in a case-by-case approach, to understand how to design automated systems that are better suited for the human driver.

8.3.3 Considerations about driving simulator experiments

Due to the need on this research project to systematic manipulate factors that might affect drivers' gaze behaviour during a transition of control, this research opted to use a 6-degree-of-freedom driving simulator as the source of experimental data. The control of the driving simulator environment allowed the experiments to specifically measure the effects of the studied variables with precision, without endangering the human driver. Also, when compared to real-world data, the output of an advanced driving simulator has higher resolution, and less noise in the data collection, which directly influences the output of the models described in this thesis.

It is acknowledged that drivers' behaviour in a driving simulator environment is not always directly equivalent to their actual behaviour on the real road (as suggested by Morando, 2018), especially in terms of risk taking behaviour. On the other hand, the University of Leeds Driving Simulator provides high levels of fidelity in terms of perceptual, and physical representation of a real world scenario. In addition, recent real world studies in this context have found very similar visual scanning patterns to those observed in previous driving simulator studies.

8.3.4 Considerations about post-hoc analysis of previously collected datasets

As already stated previously, all the analysis reported in this thesis was made post-hoc, on previously collected data from past studies. Although similar, the research goals for those studies were not perfectly aligned with the ones proposed in this document. The choice for this approach was made due the fact that this research explored the effect of different systematic manipulations of takeover conditions on drivers' structures of attention, during a takeover scenario. That said, it would not be feasible (or monetarily efficient) to perform many individual experiments over the course of a single PhD research. The Institute for Transport Studies (ITS) of the University of Leeds has at its disposal a vast array of past studies, which collected eye tracking data of drivers in transition of control scenarios, without necessarily using it. Therefore, it is believed that it was an efficient and novel way to answer the research questions and overcome the barriers imposed by the project's scope.

As a counterpoint, the approach presented several disadvantages, that should be discussed here: Since the experimental datasets used were not consistent amongst themselves, many research methods and metrics needed to be adapted from one experiment to the other, as the eye-tracking technology used for both experiments were different. This issue ultimately ended up limiting the interpretation of the outcomes of the data together, since the results were not directly comparable. Another issue that limited the comparison of the data is the fact that the researcher had no control on the experimental design choices for the datasets. With that, several statistical considerations had to be made to account for unintended experimental manipulations.

To compensate for the consequences, this experience taught the researcher a valuable lesson about interpretation of findings: since the data was not exactly perfect for every single scenario, it was necessary to learn how far your results can go. For example, the limitations and assumptions highlighted by the model, presented in section 7.5, or the considerations about the first research question, in section 8.2.1. Those considerations were made, taking into account the limitations on the different study designs for the data collected, forcing the author to think about the work, and not to rely only on statistical comparisons to draw conclusions for the thesis. On In the end, valuable theoretical considerations are drawn from this research, which relied on the abstraction power of the researcher to link distinct experiments, based on their own research questions.

8.4 Contributions to the Field

Human factors research on transitions of control from vehicle automation is constantly growing but is still a relatively new research area. Therefore, it is not yet clear how theories such as those related to situation awareness, and visuomotor coordination, interact with other work used in this context, such as decision-making theory, and models of visual attention selection. Nonetheless, the main contribution of the research reported in this thesis was to provide a broader understanding of how drivers use visual information to make a decision to take over from automation. With this knowledge in hand, it is believed that system designers may have better resources to develop human-centred products, taking into account the effects of their choices on drivers' gaze behaviour. The following sections will discuss in detail how this research can contribute to each individual field of knowledge.

8.4.1 Contributions to the experimental research field on visual attention during vehicle automation

The output of Chapter 2-5 of this thesis provided in-depth considerations about how drivers' visual attention selection is affected by the most prominent factors in the literature that may be related to the process of transition of control in vehicle automation (such as involvement with the decision-making and control loops, and the presence of information on the vehicle's HMI). The findings of this part of the research may contribute to future human factors studies in the field, by providing evidence of how attention structures may present themselves during the context of transitions of control. In other words, by understanding how different aspects of the transition process affects drivers' gaze behaviour, new studies can be developed, targeting the observed effects with supportive tools (e.g., interface design).

8.4.2 Contributions for the theoretical field of decision-making

Most of the work related to gaze and decision-making have been developed in market research studies (Krajbich et al., 2012), military sciences (Gold & Shalden, 2002), or applied research on gambling (Orquim & Loose, 2013). This research makes a contribution to the field bridging the gap between the concept of evidence accumulation (Ratcliff et al., 2016) and situation awareness (Endsley, 1995), as well as showing how decision-making models are applicable to research in vehicle automation.

8.4.3 Contributions for the methodological research on visual attention

The paper described in Chapter 3 of this research revisited the approach used by Chapman & Underwood (1998), and provided a new tool to observe drivers' attention selection patterns, that may be used in future research in the field. The technique was used in Chapter 7 for the development of a new model structure, to generate Monte Carlo simulations of drivers' gaze behaviour. It is believed that this technique may also be used in future research, to understand structures of attention in a driving environment, based on simulations created from empirical data.

8.5 Final Conclusion

This programme of research studied how visual attention during a transition of control is affected by different aspects of the driving environment, and how gaze can be correlated with the decision-making process to resume control from an automated vehicle in different driving scenarios. The research concluded that, in general, the structure of drivers' gaze is mainly influenced by the demands of the task, which is dependent on their choice/course of action during the transition process. In that sense, this research was also able to demonstrate that individual differences, in terms of gaze behaviour, can significantly affect drivers' performance in a takeover.

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