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Drivers' Willingness to Engage Level 3 Vehicle Automation

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Abstract

Automated driving has the potential to achieve improvements in road safety, and Level 3 (as classified by the Society of Automotive Engineers) vehicles are expected to be the gateway towards higher levels of vehicle automation. In many driving situations, the driver of a Level 3 vehicle will have a choice of vehicle control mode - automated or manual. The driver's willingness to delegate the driving task to an automated system is a key factor likely to determine the ultimate success of vehicle automation. As limited research has investigated this topic, this thesis focusses on the investigation of factors that influence drivers' willingness to engage automated driving (WTE) in Level 3 automated vehicles during non-critical (everyday) driving. The human factors literature into automated driving was surveyed and a suitable theoretical framework selected and adapted to specifically address issues related to WTE. Guided by the adaptation of the theoretical framework, factors that have the potential to affect WTE were identified and hypotheses developed. Thereafter, four experiments were conducted as part of the research presented in this thesis.

The experimental research was conducted in a purposely-developed driving simulator which was validated in the first study of the research program. The study also identified driving situations and conditions that were suitable for research of vehicle automation in the driving simulator. The second study explored the subjective perception of levels of situation complexity and traffic density among drivers. Results show that there was a significant disagreement between raters, especially in levels of situation complexity. These findings were used to formulate guidelines for the development of driving simulator scenarios in this research project. Study 3 examined drivers' WTE, stated willingness to resume control of the vehicle (WTRC) and perception of safety (POS) under variable experimental conditions: situation complexity, speed and vehicle control mode. Results revealed a strong negative effect of situation complexity on WTE (positive effect on WTRC) and POS while other external factors had a lesser effect. Trust in automation was identified as a significant positive predictor for WTE (negative for WTRC) while driving enjoyment was a strong negative predictor of WTE (positive for WTRC). Study 4 observed drivers' choice of driving mode when being exposed to the same driving situations, and levels of situation complexity, used in Study 3. The study confirmed WTE as a predictor of driver's behaviour in Level 3 automated vehicles. It also found a strong positive effect of first exposure to vehicle automation on the acceptance of automated driving and identified trust in automation as a strong positive predictor of choice of automated control mode. Based on the analysis of participants' comments, driver confidence was identified as a negative predictor of automated driving.

This research made significant theoretical contributions to the adapted theoretical framework, identifying new links between investigated constructs and suggesting the inclusion of additional variables. This was arguably the first experimental research program that explicitly addressed this topic and provided several practical implications of the findings and recommendations for future research. Considerable methodological contributions regarding automation simulator development were also made.

Declaration

This thesis is an original work of my research and contains no material which has been accepted for the award of any other degree or diploma at any university or equivalent institution and that, to the best of my knowledge and belief, this thesis contains no material previously published or written by another person, except where due reference is made in the text of the thesis.

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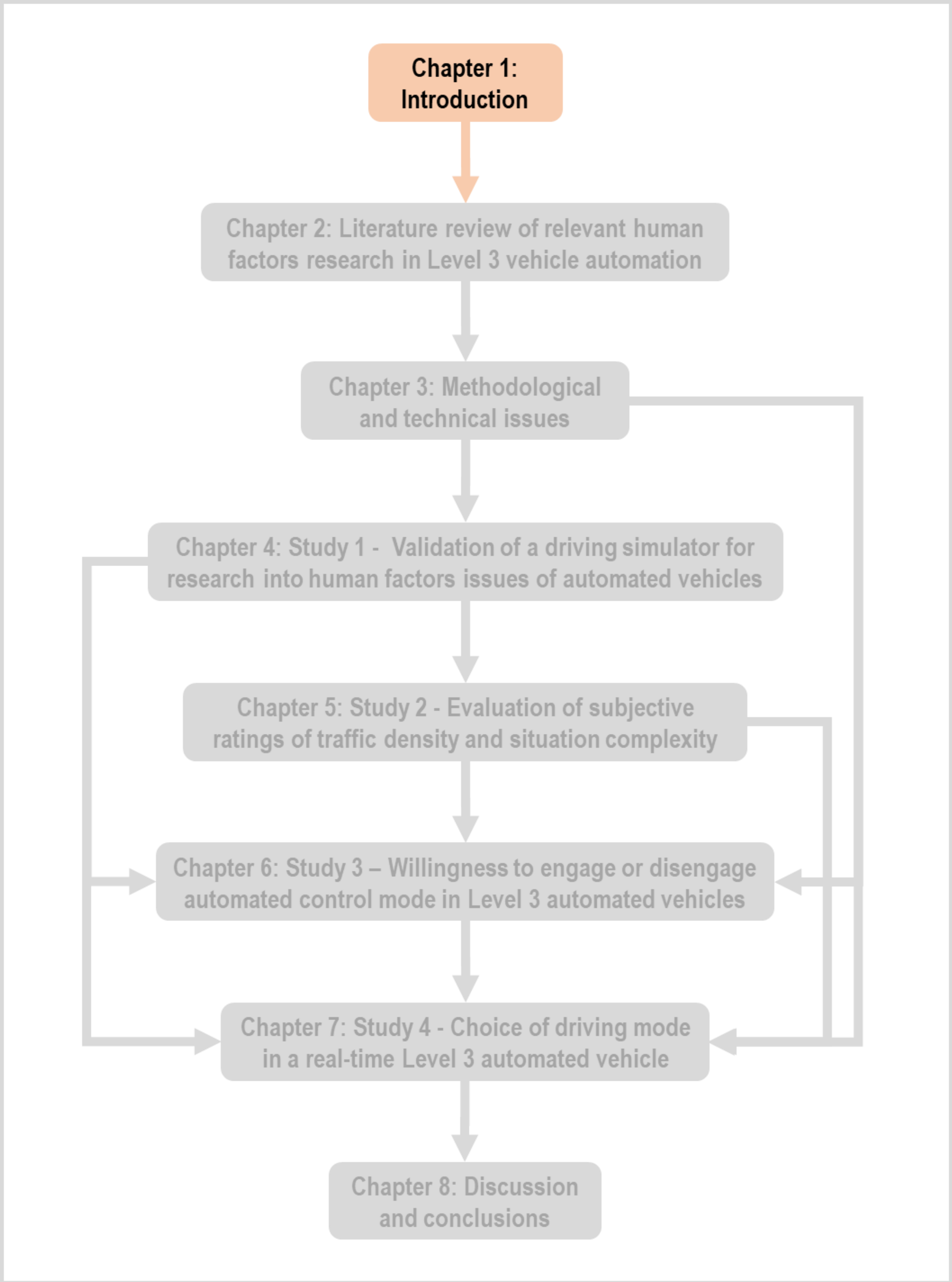
List of Acronyms

ABS	Anti-lock Braking System
ACC	Adaptive Cruise Control
AD	Automated Driving
ADS	Automated Driving System
ADAS	Advanced Driver Assistance System
ADR	Australian Design Rules
API	Application Programming Interface
AS	Automated System
AV	Automated Vehicle
DDT	Dynamic Driving Task
DMI	High-Definition Multimedia Interface
ESC	Electronic Stability Control
FOV	Field of view
Free	Free driving simulator scenario event
GEE	Generalising Estimating Equations
GFOV	Geometric Field Of View
GUI	Graphical User Interface
GW	Give Way simulator scenario event
HFOV	Horizontal Field Of View
HMI	Human-Machine Interface
HUD	Head-Up Display
LF	Low Frequency
LHD	Left-Hand Drive
LKA	Lane-Keeping Assist
LPE	Lateral Position Error
MUHREC	Monash University Human Research Ethics Committee
OC	Oncoming Car simulator scenario event
ODD	Operational Design Domain
PAC	Proportion of Automated driving Choices
PAD	Proportion time spent in Automated Driving
PID	Proportional-Integral-Derivative
POS	Perception Of Safety
RF	Rain and Fog simulator scenario event
RHD	Right-Hand Drive
SAE	Society of Automotive Engineers
SC	Situation Complexity
TD	Traffic Density
TH	Time Headway
USB	Universal Serial Bus
VF	Vehicle Following simulator scenario event
WTE	Willingness To Engage automated driving system
WTRC	Willingness To Resume manual Control of the vehicle

CHAPTER 1



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Chapter 1 Introduction

1.1 Problem statement

1.1.1 The complexity of driving

Driving is a very complex activity. A wide range of skills and abilities are required for safe driving (Horberry et al., 2006), often while conditions are not ideal. It is not always the case that the driver is trained, experienced, rested, well-behaving and free of distractions. Also, there are other participants in the traffic system with their own imperfections. Interactions between traffic entities are many, not always predictable and require a long time to learn and master. The number of vehicles on the roads is continuously increasing, making driving even more complex (Baldwin & Coyne, 2003; Hao, Wang, Yang, Wang, Guo, Zhang, et al., 2007).

In addition to increasing traffic density, drivers are subjected to the introduction of new information, communication and entertainment technologies inside the vehicle. Silva (2014) concluded that as a result of these trends, the driving task has increased in complexity and faces new challenges. Other researchers identified problems with a surge of in-vehicle information technologies such as Engström et al. (2005) who stated that in-vehicle information systems introduce secondary tasks that compete with the primary driving task, potentially causing excessive workload and distraction. Similarly, Schneegass et al. (2013) observed an increase in complexity of driving, concluding that new car features that can be used in addition to the primary driving task, (e.g. communication and entertainment) may increase driver's workload. An increase in mature-age driving population in developed countries also represents a problem as they are particularly susceptible to an increase in driving task complexity. Loss of cognitive and physical abilities in this group who, in the desire to maintain independence, continues to engage in driving despite being more prone to accidents (Stamatiadis & Deacon, 1995). Deaths of road users older than 65 years increased by 2.2% annually over the last decade in Australia (BITRE, 2020).

Worldwide, road traffic fatalities are increasing (World Health Organisation, 2018). In 2016 the total number of road traffic deaths was 1.35 million although the death rate relative to population is constant It is estimated that traffic fatalities cost US$260 billion each year and that accident injury account for another US$365 billion. This represents a total of US$625 billion annually from highway fatalities and injuries (MSR, 2016).

The latest statistical report on road trauma in Australia (BITRE, 2020), show that the number of road deaths per year increased between 2014 and 2016 followed by a decrease in both 2017 and 2018, but increased again by 5.3% in 2019. This number of fatalities represents a significant offset (13%) from the target set by the National Road Safety Strategy 2011-2020. Even when an increase in population is taken into account, there have been no significant improvements since 2014 (**Figure 1.1**). On a global scale too, there is a lack of progress in achieving the Sustainable Development Goal (SDG) target 3.6 of a 50% reduction in road traffic deaths by 2020 (World Health Organisation), 2018). These facts suggest that conventional road safety measures might have reached the limit of their effectiveness.

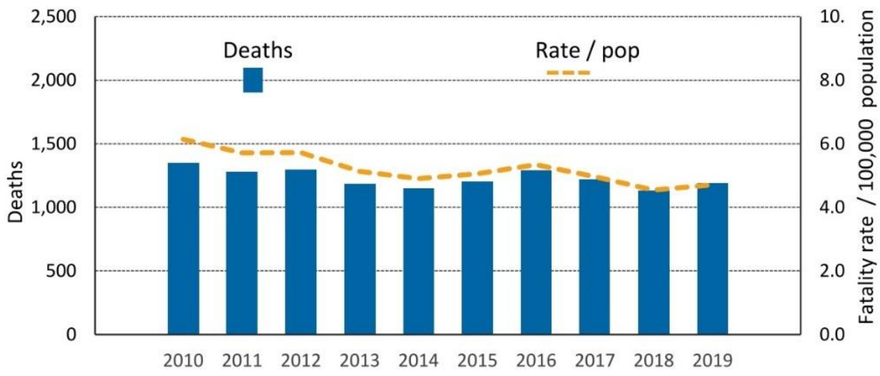

Figure 1.1 *Road fatality rate per 100,000 population 2010-2019. Source:* (BITRE, 2020)

In summary, a new technological/regulatory intervention (similar to the introduction of seat belts, and later ABS and ESC) might be required to further improve road safety. Automated driving has the potential to achieve such improvements (Young et al., 2016).

1.1.2 The emergence of automation in driving

Vehicle automation has become a globally popular topic in recent years (Drury et al., 2017; Gordon & Lidberg, 2015). Automated vehicles (AV), autonomous vehicles, self-driving cars, connected vehicles, cooperative intelligent transport systems and automated driver support systems are some of the terms associated with this revolution. The Oxford English Dictionary defines automation as "*the use of electronic or mechanical devices to replace human labour*". Parasuraman, Sheridan and Wickens (2000) emphasised human-machine comparison in their definition of automation: "*a device or system that accomplishes (partially or fully) a function that was previously, or conceivably could be, carried out (partially or fully) by a human operator*" (p. 287). The most relevant definition referring to automation in vehicles is provided by SAE International (2018) who defined Automated Driving System (ADS) as "*The hardware and software that are collectively capable of performing the entire dynamic driving task (DDT) on a sustained basis, regardless of whether it is limited to a specific operational design domain (ODD)*" (p. 3).

Although modern cars have been becoming increasingly more sophisticated with time, there is significant variation in predicted implementation timelines of fully automated vehicles, ranging from 2025 to 2075 (Shladover, 2016). While there were attempts to create an automated vehicle in the past, only recently are such vehicles becoming a reality as more advanced automation to assist and supplement the driver is developed (Trimble et al., 2014). Driven by available technological advances and the battle for profits, all major car manufacturers, including technology companies previously not associated with cars, are competing to produce commercial automated vehicles.

It can be concluded that the development of automated cars promises new hope for traffic safety. However, it also raises important human factors research questions regarding the acceptability of that technology, driver trust, intentions of use, ease of use and even optimisation of the human-machine interface (Birrell et al., 2014; Lau et al., 2018; Payre et al., 2014). Despite such concerns, it is generally accepted that the social benefits of automated vehicles will outweigh likely disadvantages: these are further explored in section 1.1.4.

1.1.3 Levels of automation

SAE (Society of Automotive Engineers) has introduced a taxonomy that identifies different levels of vehicle automation (SAE International, 2018). This classification has been widely accepted in the literature and will be used in this document (see **Table 1.1**). The table illustrates who has responsibility for various aspects of driving, gives estimates of the percentage of automated driving as well as deployment predictions. For each level of automation, the red human-shaped icon indicates that the task is performed by the human driver while the blue car-shaped icon indicates that the task is performed by the vehicle automation system.

Table 1.1 *Levels of Automation (human and car icons indicate who is responsible for the particular task), adapted from* (SAE International, 2018)

Automation level	**0**	**1**	**2**	**3**	**4**	**5**
Level name	No automation	Driver assistance	Partial automation	Conditional automation	High automation	Full automation
Vehicle control						
Environment monitoring						
Emergency control						
Automated driving %	None	Isolated actions	Some	Significant	Mostly	All
Likely deployment	1886/1917[1]	1958[2]	2000[3]	>2020[4]	>2040[5]	>2070[5]

[1] (Stein, 1967), [2] (Chrysler, 1958); [3] (Mercedes Actron, 2000), [4] (Dowling, 2020; IEEE, 2020), [5] (Shladover, 2016)

Vehicle longitudinal and lateral control was the first driving task to be automated. Examples of Level 1 automation include cruise control, ABS (anti-lock braking system) and automated parking. In Level 2 automation, aspects of driving such as speed, distance from objects in front and lateral position within a driving lane is controlled by the automation. In Level 3, which is the focus of this thesis, automation can change lanes and make turns. Automated monitoring of the roadway environment starts at Level 3, but the driver is required to remain 'in the loop' due to the responsibility to resume manual control in the case of an emergency. The percentage of automated driving will increase with each level of automation. The likely deployment date of each level beyond Level 2 remains speculative. Until all vehicles on roads are automated and connected there is going to be a long period of mixed traffic.

Early deployment predictions for Level 3 automation have proven to be overly optimistic, suggesting the issue is more complex than previously assumed. Kalra and Groves (2017) proposed that highly automated vehicles be allowed on roads once they are judged to be safer than an average human driver. However, the more realistic scenario is that the safety benefits of automated vehicles will need to be supported by evidence as being significantly safer. Martens and Van Den Beukel (2013) predicted that until AVs are completely reliable and safe under all conditions, the human driver will remain responsible for safe driving. Nitsche et al. (2014) identified legal prerequisites, precise geolocation/map data and robust driver state monitoring to hand over control, connectivity between vehicles, road users and infrastructure as well as the optimal interaction between automated and non-automated vehicles as *"major enablers for the safe and efficient operation of automated transport"* (p. 3).

1.1.4 Benefits of automated vehicles

There is a wide range of benefits that AVs (automated vehicles) are likely to bring to society. They range from significant improvements in road safety to positive impacts on the economy and general quality of life.

More specifically, AVs may contribute to a reduction in the number and severity of road crashes (Young et al., 2016). This reduction will result from the likely elimination or reduction of the human error causes of vehicle crashes (Haboucha et al., 2017). The introduction of AVs is predicted to result in more efficient parking, narrower lanes and generally increased road capacity that would lead towards a reduction in congestion (D. Metz & David, 2018). Driving in platoons is another way of reducing congestion (Gouy, 2013). Vehicle platooning will also reduce fuel consumption. Increased fuel efficiency is predicted through more efficient driving compared to human driving as well as significantly improved efficiency by higher vehicle utilisation in shared systems (Beiker, 2014). This efficiency can be achieved by vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communications, allowing prediction of traffic patterns, and optimising vehicle accelerations and decelerations and path selection.

AVs can also provide benefits in terms of time efficiency and efficient use of resources. Widely available car-sharing would reduce the number of privately-owned cars reducing the total number of cars (Shaheen & Bouzaghrane, 2019). Indirectly, car-sharing may extend the reach of public transport (Litman, 2020).

Another important benefit is increased mobility and therefore, independence, for non-drivers such as elderly, and disabled (J. Yang & Coughlin, 2014). Drivers may be able to use the commuting time for work and other activities (Yim, 1997; Bay, 2016). It is expected that travel times will be reduced as a result of efficient route planning (Litman, 2020). Driver comfort may also be increased due to lower levels of workload (de Winter et al., 2014).

1.1.5 Potential problems of automated vehicles

Despite the many potential benefits, automated vehicles are also likely to bring many challenges. The Geneva Convention on Road Traffic from 1949 and Vienna Convention on Road Traffic 1968 state that a vehicle must have a driver who is able to control it. This is one of many issues that will have to be addressed before AVs (automated vehicles) can be deployed. Barabás et al. (2017) observed that there is still a gap between automated vehicle technology and current regulations; however, this gap is continuously reducing. An example of this is the amendment from 2017 that introduced the concept of autonomous steering, thus facilitating automated driving.

As with the introduction of any new technology, it is expected that the initial costs of automated vehicles will be high compared to conventional vehicles as AVs contain additional vehicle equipment which would require additional service and maintenance (Litman, 2020). Upgrades to the road system and infrastructure will also be required; these high costs might influence customer acceptance of the AVs (Woldeamanuel & Nguyen, 2018). A long transition period is expected; there is going to be a mix of autonomous and human driving for a substantial time (Young et al, 2016). Understanding of human behaviour and signals by AVs and vice versa, understanding of AVs behaviour by humans will be the key issue during this period. There are a plethora of legal questions about how mixed traffic will be regulated. Questions such as who assumes responsibility in the case of an AV with conditional automation (Level 3) crashing, law enforcement interactions with AVs, instances of vehicle automation algorithms facing ethical problems, the ability of vehicle automation to read and interpret human gestures and many others will require modifications to the legal framework and changes to insurance models (Fraedrich & Lenz, 2016).

AVs could also be abused in the form of criminal and terrorist attacks (Beiker, 2014). For example, an AV can be used as a method of explosive device delivery. There are obvious privacy concerns such as potential hacking, unauthorised tracking and data sharing (Litman, 2015). AVs are likely to collect travel information including video recordings of driving. Employment and business activity will experience major changes (Dosen et al., 2017), with an expected decline in driving and vehicle repair jobs (Pokutta & Lee, 2015).

Loss of driving proficiency and experience among the general population is also of concern (Marinik et al., 2014; Saffarian, de Winter, et al., 2012). The incidence of carsickness during automated driving could present a problem (Diels, 2014) due to increased involvement in non-driving tasks and resultant sensory conflict (Ihemedu-Steinke et al., 2018), user interface designs and use cases (Smyth et al., 2021). Also, the adoption of AVs could present a challenge for the older population due to loss of cognitive skills and anxiety associated with using new technology (Souders & Charness, 2016).

Effects of weather conditions (Lavasani, 2017) on AV operation are still not well understood. More convenient and affordable travel may increase the total amount of travel which would then contribute to the increased cost of parking, crashes and pollution and increase travel time due to suburbanisation (Woldeamanuel & Nguyen, 2018). Focussing on AVs may adversely affect the implementation of conventional cost-effective modes of transport (Litman, 2015). It has also been speculated that computer malfunctions could produce worse crashes than a human driver (Shladover, 2018), while safety for non-automated vehicles might worsen during the mixed traffic transition period (Sivak & Schoettle, 2015).

1.1.6 Human factors issues

Despite ongoing developments in vehicle automation, automated vehicles (Level 3 and above) are still not widely available commercially. Saffarian et al. (2012) commented that challenges of vehicle automation are *"more than technical"* (p. 1). They referred to human factors issues of safety, usability, acceptance and more. Moreover, these problems are often more difficult to resolve than technological ones. This section summarises some general human factors issues, whilst the specific issues relevant to the research questions of this thesis are presented in Chapter 2.

There are many human factors issues related to vehicle automation currently being investigated by researchers around the world. One of the most important issues is driver **over-reliance on automation**, also referred to as **automation complacency**. Parasuraman and Manzey (2010) operationally defined complacency as *"poorer detection of system malfunctions under automation control compared with under manual control"* (p. 9). The problems associated with overreliance arise when the automated system is no longer active and the driver is unable to adapt to changes in the driving task (Creaser & Fitch, 2015).

Driver trust is important for the appropriate use of automation. Some of the issues are distrust and overtrust (Lee & See, 2004). Distrust occurs when driver underestimates capabilities of the automated system and decide not to use it while overtrust occurs when the driver overestimates the capabilities of the automated system and choose to use it in inappropriate conditions.

Behavioural adaptation occurs when a driver's perception changes as a result of long-term exposure to automation. For example, with the perceived safety benefits of automation drivers might increase their threshold of risky behaviour. Also, drivers are likely to engage in non-driving activities when driving automated vehicles.

Skill degradation occurs when a particular task becomes automated and it is likely to increase with the introduction of higher levels of vehicle automation. This is a problem in situations where a driver is required to take over control of the vehicle. Such take-over requests present a sudden increase in driver workload potentially exceeding the driver's capacity to respond adequately (Fuller, 2005; Martens & Van Den Beukel, 2013).

Driver acceptance of automated vehicles is another important issue as the success of automated vehicles is dependent on acceptance by users (Nordhoff et al., 2018). In their investigation of acceptance of advanced vehicle systems, Crump et al. (2016) concluded that despite obvious benefits of automated driving, its effectiveness will be diminished if drivers disable the automated system or fail to understand operational design domain of the automated system.

All these and related issues emphasise the importance of the **Human-Machine Interface** (HMI) in automated driving. Young et al. (2016) identified a need to resolve HMI issues to make automated vehicle technology usable and effective, while at the same time preventing driver overload or distraction. Other human factors issues include **driver distraction, loss of situation awareness, mental workload,** and **driving in mixed traffic**.

An overview of recent publications shows that most of the human factors research in automated driving is directly or indirectly, focusing on the critical situations and take over requests while no or very little research was dedicated to non-critical driving. However, non-critical situations represent a vast majority of the driving and acceptance of automated driving in these conditions is likely to be one of the key facilitators to the true adoption of automated vehicles (Regan et al., 2014).

Several simulator and on-road studies presented drivers with everyday driving in AVs and the facility to freely engage and disengage automated systems. In their study Metz et al. (2021) explored naturalistic, self-chosen usage of automated driving systems focussing on changes in acceptance and usage with repeated exposure. In a study on the effects of knowledge about the capabilities and limitations of the automated system on trust in automation (Khastgir et al., 2018), participants were able to transition in and out of automated driving mode anytime they desired, rather than at scripted simulator events. In a naturalistic driving study that used vehicles equipped with adaptive cruise control, lane keeping assist and other systems Noble et al. (2021) investigated changes in driver behaviour when engaging these systems. They compared eye glance behaviour and secondary task engagement between instances when driver assistance systems were active and instances when they were inactive. A simulator study by Jamson et al. (2013) presented participants with the ability to freely engage in automated driving and observed their behaviour and uptake of secondary tasks. In their simulator study on the impacts of fatigue on automated driving Neubauer et al. (2012) presented participants with the voluntary choice of vehicle control mode. Despite presenting a real-time interactive automated driving and everyday situations in both simulator and on-road, none of the above studies specifically looked into drivers' decisions to engage vehicle automation or resume manual control of the vehicle.

Therefore, this thesis focuses on everyday driving and what factors influence the driver's willingness to engage automated driving under these particular circumstances in Level 3 automated vehicle.

1.2 Research aims and questions

The principal aim of this research is to evaluate some of the factors that influence drivers' willingness to engage automated vehicle control mode (WTE) when driving in manual control mode and willingness to resume manual control (WTRC) when driving in automated control mode of a Level 3 automated vehicle in everyday driving situations. Since the investigation of vehicle automation fallbacks was not one of the research aims, WTRC that was observed during automated driving that did not involve takeover requests by the system. Experimental work plans to observe the driver's WTE and WTRC under variable external conditions followed by the observation of the actual driver's behaviour in a real-time simulated Level 3 automated vehicle. Additionally, the thesis aims to investigate the effects of driver characteristics on the preference of vehicle control mode.

The majority of the research program was designed to be conducted in a simulator for automated driving. Therefore, a secondary aim of the project was the partial behavioural validation of the simulator for conducting specific human factors research into vehicle automation. This was considered important since simulator validation studies in the context of automated driving are very rare and field operational trials (FOTs) using automated vehicles were not practical in Australia at the time this research was conducted.

The specific research hypotheses will be presented at the end of Chapter 2 following the literature review, but the overall research questions to be explored in this thesis are:

- What are the factors that influence drivers' WTE or WTRC?
- Which driver characteristics are likely to affect WTE?
- Can a medium fidelity driving simulator be used as a research tool for human factors research in vehicle automation?

1.3 Scope of the research and contributions to knowledge

It has been widely acknowledged that Level 3 vehicle automation presents a unique set of challenges for legislators, car manufacturers and drivers. From a human factors point of view, problems associated with higher levels (4 and 5) of automation are much simpler since the ADS (automated driving system) must be *"capable of automatically performing the DDT fallback as well as achieving a minimal risk condition"* (SAE International, 2018, p. 25). As a result of this requirement, many of human factors issues, associated with Level 3 automation become less relevant by default. Hence, higher levels of automation were outside the scope of this current research.

The experimental work in this thesis focuses on the factors that influence drivers' WTE (willingness to engage in automated driving) when in manual driving mode and, alternatively, WTRC (willingness to resume control of the vehicle) when in automated driving mode. In addition to selected external factors, the effects of driver characteristics on the preference of vehicle control mode were examined.

The research is primarily focused on everyday driving situations and preferred vehicle control mode in these situations. Therefore, important issues such as forced transfer of control, critical situations, and engagement in secondary tasks were not directly within the scope of this research. Although identified as one of the possible factors for the acceptance of automated vehicles, car sickness was also outside the scope of the research due to range of complex technical and ethical issues associated with conducting such studies.

This work aims to contribute to the general knowledge of automated driving, particularly for Level 3 automation as it attempts to identify driving conditions, subjective perceptions and driver characteristics that determine the choice of Level 3 automated vehicle control mode in non-critical (everyday) driving. Also, it will attempt to validate a newly-developed driving simulator for research in to the human factors associated with automated driving, contribute to existing theoretical models of driver behaviour in automated vehicles and acceptance of vehicle automation.

1.4 The structure of the thesis

The thesis is organised into eight chapters. Within it, four experimental chapters are presented, documenting progress from the initial validation study to the quasi-naturalistic observation of driver behaviour in a simulated automated vehicle.

Chapter 2 reviews the background literature on what is known about automated driving such as surveys, human factors research, providing a theoretical framework and identifying a gap in knowledge. It also presents the research hypotheses.

Chapter 3 summarises work done on resolving a range of methodological and technical issues undertaken to facilitate experimental studies using a simulator and on-road vehicle.

Chapter 4 describes the driving simulator validation study (Study 1) that introduced the driving simulator as a tool for research into human factors of automated driving, as well as issues relevant to the design of future simulator scenarios.

Chapter 5 describes an exploratory study (Study 2) comparing the subjective perception of traffic density and situation complexity among different raters. This study aimed to provide guidance for the design of future studies in terms of experimental scenarios and selection of independent variables.

Chapter 6 describes a simulator study (Study 3) investigating the driver's self-reported WTE, WTRC and perception of safety when driving a Level 3 automated vehicle under variable conditions.

Chapter 7 describes a simulator study (Study 4) investigating actual driver behaviour and choice of control mode in a Level 3 automated vehicle. Dependent variables were the choice of driving mode, the percentage of time spent in automated driving mode. Effects of exposure to automated driving were examined using questionnaires.

Chapter 8 contains the general discussion and draws together the results of the entire research program and discusses the practical and theoretical implications of the findings and discusses further research directions.

The flowchart (**Figure 1.2**) illustrates the logical links between chapters of this thesis, presented in chronological order (from top to bottom).

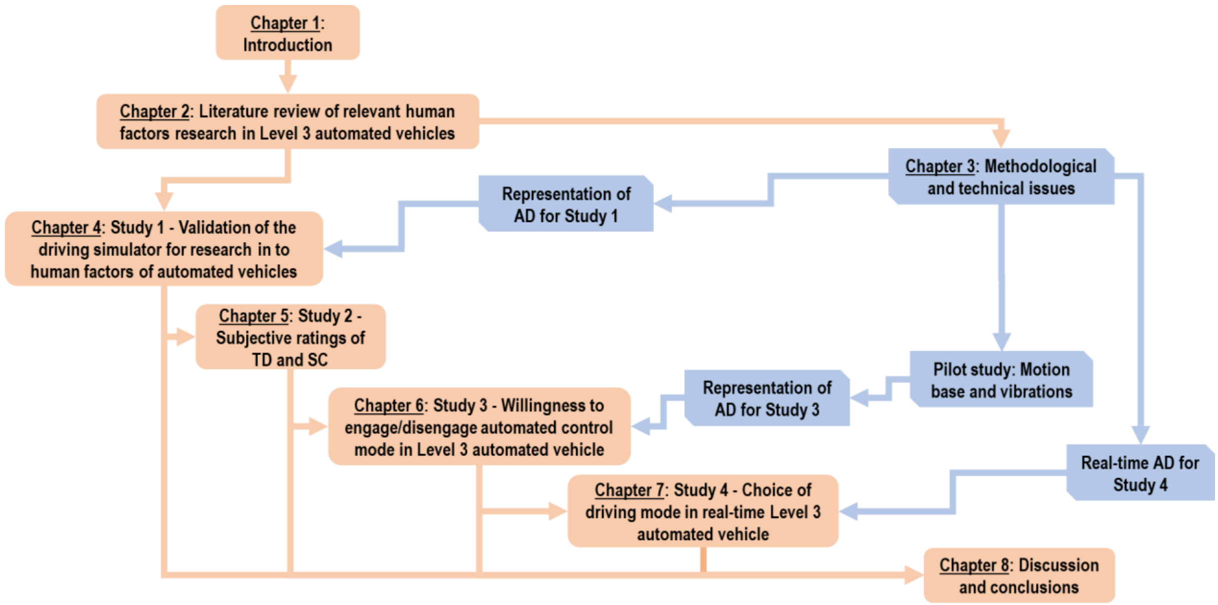

***Figure 1.2** The thesis overview flowchart*

In **Figure 1.2**, the blue coloured shapes in this flowchart are part of Chapter 3. They indicate supporting activities (methodological and technical solutions) conducted to facilitate experimental studies. At the beginning of each chapter, a simplified flowchart illustrates the placement of the chapter and links with other chapters within the thesis.

In this chapter and the overall thesis, to improve the clarity of the text, the acronym WTE will be used for driver's willingness to engage vehicle automation, and unless investigated independently, WTRC (driver's willingness to resume manual control or disengage vehicle automation) as they are fundamentally antipodes.

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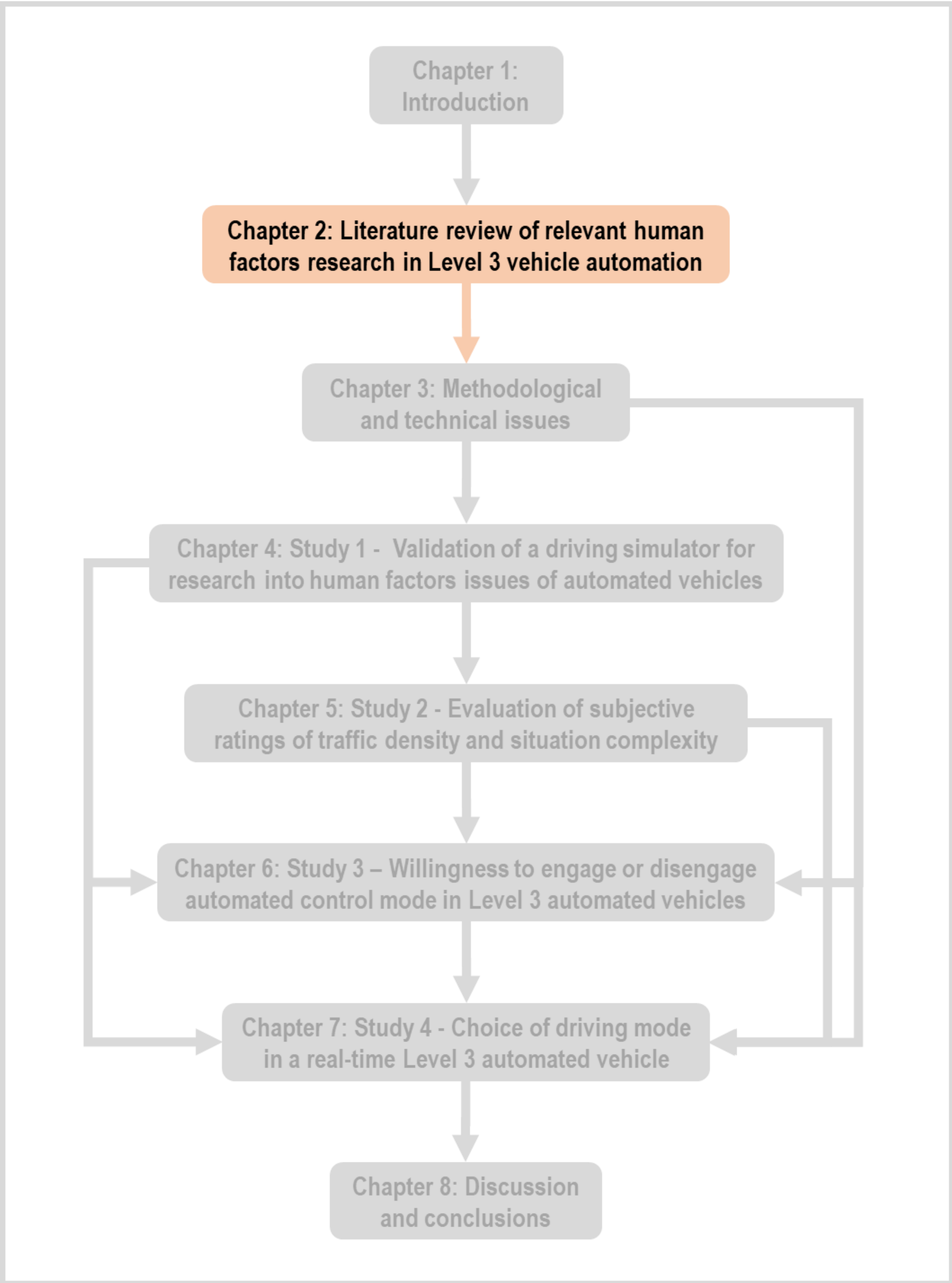
CHAPTER 2


Chapter 1: Introduction
Chapter 2: Literature review of relevant human factors research in Level 3 vehicle automation
Chapter 3: Methodological and technical issues
Chapter 4: Study 1 - Validation of a driving simulator for research into human factors issues of automated vehicles
Chapter 5: Study 2 - Evaluation of subjective ratings of traffic density and situation complexity
Chapter 6: Study 3 – Willingness to engage or disengage automated control mode in Level 3 automated vehicles
Chapter 7: Study 4 - Choice of driving mode in a real-time Level 3 automated vehicle
Chapter 8: Discussion and conclusions

Chapter 2 Literature review of relevant human factors research in Level 3 automated vehicles

2.1 Introduction

The aim of this chapter is to identify and analyse current relevant human factors research that is likely to determine a driver's choice of vehicle control mode in Level 3 automated vehicles. The scope of the literature that concerns human factors of driving is vast and rapidly expanding with the emergence of vehicle automation and, as such, could not be covered in its entirety within one chapter. Therefore, this review focuses only on the presentation of a theoretical model and a review of factors that can best be correlated to the overall thesis research questions. The chapter first highlights an increase in research interest in vehicle automation over the last several decades. It then gives a short overview of broad types of methodologies used in human factors research of vehicle automation. This is followed by a selection of a theoretical model, identification of key factors and review of previous research done on these factors in the context of automated driving. Based on this literature review a series of hypotheses are presented.

2.1.1 Research interest in vehicle automation

Research in automated vehicles has been fuelled by the pace of technological developments in this field. The number of publications concerned with automated driving has been increasing as the date of launch of truly automated vehicles is approaching. This trend is illustrated in **Figure 2.1**. Cohen et al. (2017) conducted a database search using keywords and synonyms related to automated vehicles. The curve represents the number of published documents in English that contain keywords and synonyms related to automated vehicles. The most discussed topics are the driver's interaction with AV, road safety, public perception, and legal and regulatory issues.

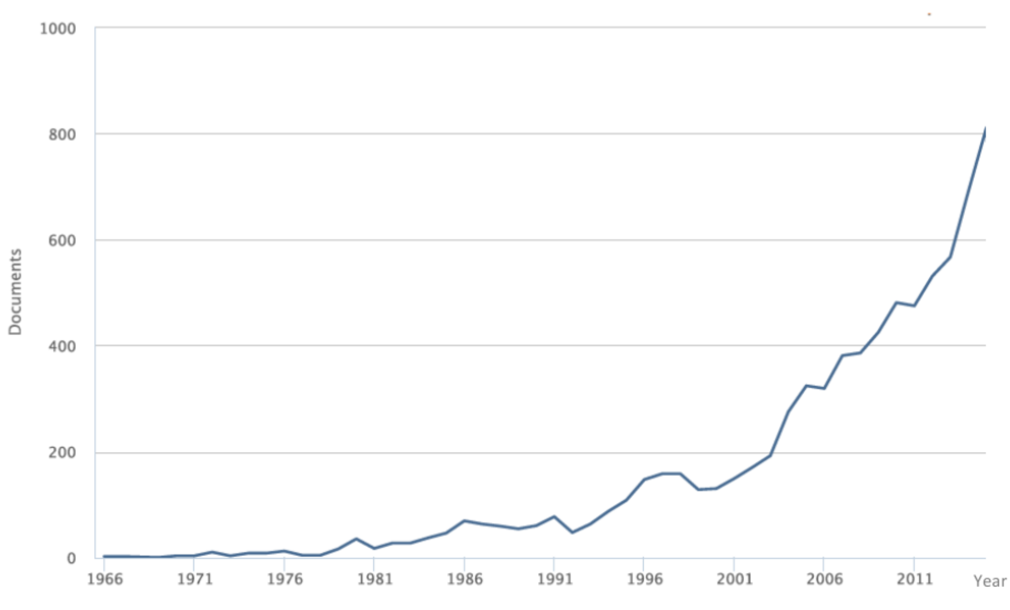


***Figure 2.1** Number of English publications on automated vehicles* (Cohen et al., 2017)

Although this curve does not discriminate between the so-called “grey” publications from the academic papers, it represents an increase of interest in automated vehicles in both media and academia. The same trend continued in the last three years as illustrated in **Figure 2.2** showing results of a Scopus database search undertaken as part of the research presented in this thesis on the number of publications that mention automated vehicles. A small drop in a number of published documents observed in 2020 is likely due to the global impact of Covid-19 pandemic on research activities.

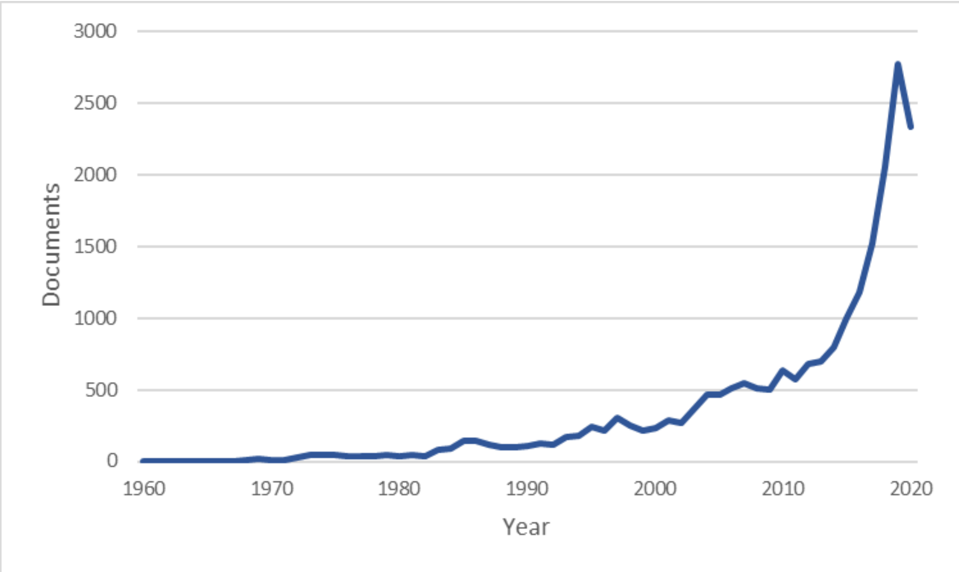


***Figure 2.2**. Scopus database search results on automated vehicles (1960 - 2020)*

2.1.2 Research methodology for investigating human factors of vehicle automation

At the time of this candidature, human factors research in vehicle automation faced many methodological and technical challenges due to lack of access to mature and implemented automated vehicles as well as and supporting technologies. A brief review of available research methodologies was therefore conducted to provide guidance in addressing some of these issues.

Human factors research employs a range of methodologies to study and measure driver behaviour (Regan et al., 2014). To generalise greatly, there are two main groups of measures. The first group refers to methods where data are collected via self-reporting. The second group of measures is objective measurements such as simulator, on-road and naturalistic studies.

Self-reporting measures

Jupp (2006) defined a self-reporting study as the one *“in which respondents report their own behaviour”* (p. 2). Examples of self-reporting data collection are surveys, interviews and focus groups. Studies based on these measures may ask participants questions about their behaviour in hypothetical situations as true AVs (automated vehicles) are still not available. Some of the commonly addressed questions were acceptance of AVs (Hulse et al., 2018; Liljamo et al., 2018; Liu, Yang, et al., 2019), willingness to pay (Cunningham et al., 2019; Daziano et al., 2017), intention to use (Choi & Ji, 2015; Payre et al., 2014) and attitudes towards AVs (Böhm et al., 2017; Hyde et al., 2017; Lee & Kolodge, 2018). They can be used to investigate perceptions of AVs, reveal occasions and situations in which AVs would be used, discover catalysts and barriers towards the adoption of vehicle automation (König & Neumayr, 2017; Liang et al., 2019). Self-reporting measures can also be used during or after simulator studies.

The main advantages of self-reporting are convenience, low cost and simplicity (Bailey & Wundersitz, 2019). Despite these advantages, the results are not always representative of actual behaviour as participants may not know how would they behave in presented specific hypothetical situations (Shaughnessy et al., 2000). Also, responses might be biased and affected by psychological limitations (Bailey & Wundersitz, 2019). Although not always producing perfect results, these methodologies are often used as the first step when a new field of research is open, such as vehicle automation and should be used as a complement to more objective methods.

Objective measures

Objective methodologies include direct observation and measurement of driver behaviour in laboratory, simulator and test track experiments, as well as on-road studies and observational studies.

Laboratory experiments allow for measurements that are impractical to collect in other settings, such as physiological responses. If designed properly they are likely to provide strong evidence of the relationship between independent and dependent variables. The main concern is that due to the very controlled setting, results may not always be generalisable to the real world. Also, experimental tasks are often artificial in comparison with real-world situations. They are useful for investigating a limited number of factors. For example, Kinnear et al. (2013) used laboratory conditions in an exploration of anticipation of road hazards. In this study, the stimuli were provided in a form of video clips.

Simulator studies are traditionally used in the investigation of human factors of driving. They allow controlled experiments for the investigation of driver behaviour in response to scenario variable manipulations. They provide a controlled and safe environment while allowing immersion in a driving task. Simulator scenarios can represent a wide range of real-world driving environments that can be repeatedly executed (Espié et al., 2005). They offer greater face validity than laboratory studies while facilitating other measurements such as physiological data. Despite numerous advantages, simulator experiments still represent a somewhat artificial task as limitations in simulator fidelity and the level of accurate representation of the real world remain observable (Espié et al., 2005; Philips & Morton, 2015). Participant motivation for taking part in the study is also a concern as it may be driven by curiosity (Carsten & Jamson, 2011; Jamson et al., 2013). The cost of achieving ultimate fidelity can be prohibitive, however, advancements in technology have been increasing the affordability of simulators.

Test tracks experiments add a level of realism when compared to simulator experiments and have been used to validate driving simulators (McGehee et al., 2000). As real vehicles are used, all real-world cues are present. However, the cost of developing such a facility for research on vehicle automation is high (Kettering University, 2016; Szalay et al., 2018).

In on-road studies, real vehicles are equipped with data logging devices that record all relevant vehicle and driver parameters. They can be conducted with the presence of a researcher (Banks et al., 2018) who also might observe their behaviour, or without the researcher being present. In these studies, participants are guided/instructed to follow a predetermined route. Such an example is provided by Godley et al. (2002) who used specific roads in their simulator validation study. Participants in a study by Lenné et al. (2011) followed a pre-determined route in the exploration of driver behaviour at rail level crossings. In comparison to test track studies, on-road studies are good for capturing driver behaviour in a more realistic environment and conditions. Therefore, an in-depth investigation of behaviour is possible. Problems with on-road studies are susceptibility to the variability of different experimental conditions such as weather, traffic density, the unpredictability of other road users' behaviours and related safety issues. Other disadvantages are limited sample size, generally high running cost and often difficult data extraction.

The common feature of observational studies is that data collection is conducted without the presence and intervention of the researcher. Naturalistic driving studies (Barnard et al., 2016; Liang et al., 2019; Regan et al., 2009) in which participants were provided with an instrumented vehicle to use over a certain time interval are such examples. Not surprisingly, these studies have high face validity as true real-world behaviour is observed. A potentially broad range of research issues can be explored. However, once instrumented vehicles are deployed researchers have no control over any aspect of the study. Other issues are complex data extraction and high cost of setting up instrumented vehicles.

Research methodology summary

Studies with high control, such as laboratory, have low face validity. At the other end of the spectrum (as illustrated in **Figure 2.3**), observational studies, have the highest face validity but the lowest level of control (Wickens et al., 1998).

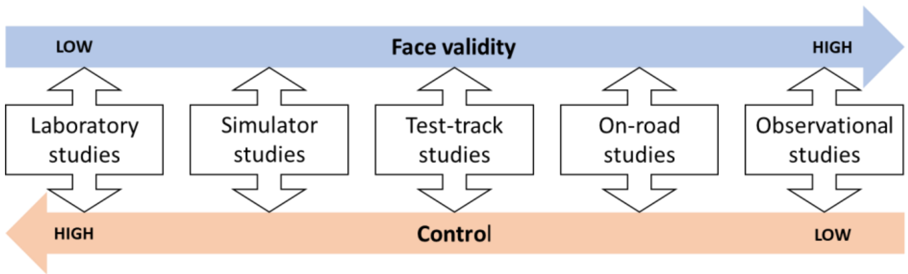


Figure 2.3 *Illustration of levels of control and face validity of different research methodologies. Adapted from (Stephan, 2015)*

Within this spectrum, simulator studies can have a relatively high internal validity while providing "*controlled settings and better oversight*" (Zoellick et al., 2019b) (p. 10). The most valid results in the exploration of behaviour in vehicle automation will be obtained only when true AVs are deployed and experienced in all real-life scenarios without supervision. At this stage, however, AVs are difficult to acquire, they are expensive, and require many ethical and safety issues associated with running on public roads to be addressed. As a result, it is not surprising that so much of the research in human factors of automated driving has been done in simulators (Eriksson et al., 2017).

2.2 Theoretical framework of driver behaviour in automated vehicles

2.2.1 Introduction to driver behaviour models for vehicle automation

Automated driving has the potential to perform tedious tasks during driving and eliminate human errors; thereby increasing road safety. However, these benefits will not materialise if drivers are not willing to engage vehicle automation (Regan et al., 2014). Many factors are likely to influence WTE (driver's willingness to engage vehicle automation). Over time, WTE might be affected by changes in driving behaviour resulting from the use of automation. Merat and Lee (2012) concluded that vehicle automation is redefining the driver's role due to the driver's adaptation to automation. Not actively controlling the vehicle, over time, can lead to changes such as loss of driving skill, reduction in situational awareness and perception of risk, overreliance, erratic mental workload and inadequate mental model of automation capabilities and potential loss of engagement in driving task (Martens & Van Den Beukel, 2013; Sullivan et al., 2016).

There is a body of empirical evidence which suggests that modifications of the driving task environment (which can include the driver, vehicle, and road) will result in changes to a driver's behaviour (Sullivan et al., 2016). The literature is full of examples showing behavioural adaptation, but these examples also show a high diversity in terms of the underlying factors and effects, which makes behavioural adaptation a complex phenomenon that is hard to predict (Gouy et al, 2014). An example of the change in driver behaviour is an increase in travel speeds as a result of improved road safety (width, delimiters) or improvement in vehicle capabilities due to the introduction of ABS and ACC (Dragutinovic et al., 2005). In their review, Sullivan et al. (2016) observed that the introduction of ADAS technologies may have further complicated the issue of driver behaviour as they *"change driving in many different, and sometimes complicated ways"* (p. 6). It can be concluded that WTE is a product of continuously evolving complex dynamic interactions between many factors. There is a variety of models in traffic psychology that address driver behaviour, for example, Fuller (2000) and Rothengatter (1997). Although discussed in the context of risk-taking and risk acceptance, such models can be applied to many aspects of driver behaviour investigation of driver's willingness to use automated driving. However, it is argued here that the theoretical framework that is capable of addressing driver's WTE needs to encompass broader concepts of driver behaviour.

2.2.2 Joint Conceptual Theoretical Framework (JCTF)

In their review of behavioural adaptation in response to driving assistance technologies, Wege et al. (2013) identified a need for a model that would capture changes in driver behaviour due to Advanced Driver Assistance Systems (ADAS). As a result, they developed a Joint Conceptual Theoretical Framework (JCTF) of behavioural adaptation in response to ADAS. It identifies relevant internal and external factors associated with behavioural adaptation focusing not only on behavioural performance changes but also on underlying internal driver processes. The authors categorised these processes as cognitive, energetic and motivational. JCTF was conceived as an integrative theoretical framework that does not focus on a specific ADAS. The main goal was to facilitate the generation of research questions and predictions about the impact of ADAS on different behavioural levels. The JCTF is illustrated in **Figure 2.4** and shows many factors *"acting simultaneously in a complex interplay"* (Wege et al., 2013, p. 14). This theoretical framework is adopted in the thesis.

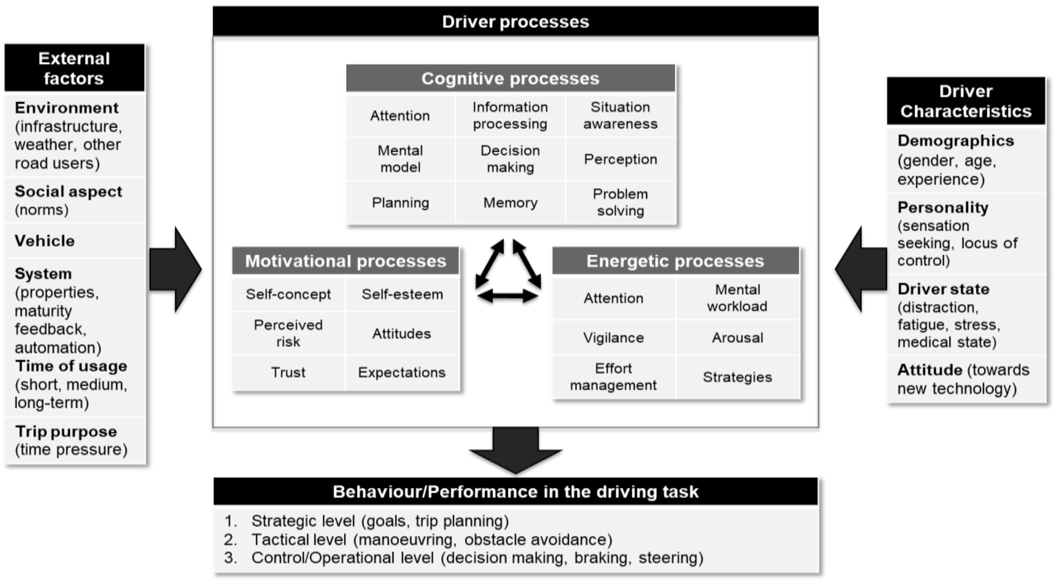


Figure 2.4 *Joint Conceptual Theoretical Framework (JCTF) in response to advanced driver assistance systems* (Wege et al., 2013)

2.2.3 Adapted JCTF for the investigation of WTE in Level 3 automated vehicle

The JCTF is very elaborate and investigation of every aspect was outside the scope for the current research. Sullivan et al. (2016) commented that JCTF was not *"specific regarding how the elements actually interact"* (p. 12), emphasising the large effort required in defining relations between constructs of the framework. This is supported by Zoellick et al. (2019), who confirmed the existence of complex relationships between different constructs that contribute to the intention to use AVs (automated vehicles). Therefore, the JCTF, applied to overall research questions of this thesis is simplified and adapted to focus on driver internal processes without looking at behavioural performance changes. This allowed exclusion of many factors and concepts that are not likely to significantly influence a driver's willingness to engage automated driving mode in Level 3 automated vehicle in non-critical driving situations. Additionally, some factors were excluded due to restrictions imposed by the limitations of selected research methodology and scope of the research.

The simplified version of JCTF applied to a willingness to engage automated driving (willingness to resume manual control during automated driving) in Level 3 automated vehicle is illustrated in **Figure 2.5**.

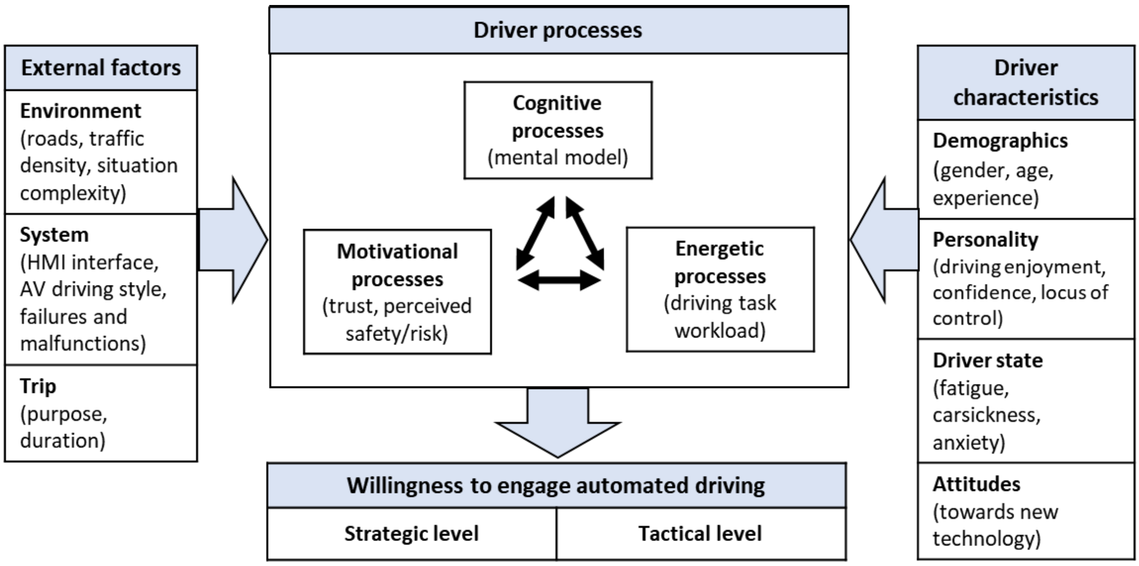


Figure 2.5 *Adapted JCTF for investigation of driver's willingness to engage automated driving*

As a result of this focus, the model was simplified by excluding factors and concepts that are not measurable, impractical for manipulation or observation or considered to have no or very little effect on the output (willingness to engage automated driving). In experimental studies, willingness to engage automated driving will be investigated primarily at the tactical level and to a lesser extent at the strategic level.

Within external factors, social aspects or norms are not considered relevant because automated vehicles are novel and such aspects are not yet substantially developed. Vehicle factors are eliminated as research is done in the driving simulator that cannot be associated with any brand of car and it is equipped with the same generic vehicle controls used by every participant. Time of usage is irrelevant in the simulator as all participants are exposed to the same conditions.

Some of the driver processes listed in the theoretical framework have been omitted in the applied model as they weren't relevant to research questions or were predicted to have only a remote effect on the principal research question. As a result, several factors within cognitive processes such as attention, information processing, decision making, planning, memory, problem solving and perception, factors within motivational processes (self-concept, self-esteem, attitudes and expectations), and factors within energetic processes (attention, vigilance, effort management, arousal and strategies) are not discussed in this review. As most of the driver characteristic can be assessed with questionnaires they were included in the discussion.

In conclusion, based on the research methodology review and the theoretical framework presented above, **Table 2.1** attempts to operationalise this theoretical model by identifying human factors and concepts that are likely to influence driver's willingness to engage or disengage automated driving under conditions defined in the overall research aims. This adaptation of the theoretical framework facilitates experimental investigation of drivers' willingness to engage in automated driving, applicable to both the strategic level and the tactical level of driving a Level 3 automated vehicle. Strategic and tactical levels are part of the hierarchy of driving tasks introduced by Michon (1985). The factors that are further explored are divided into three main groups as specified by the JCTF: driver processes, driver characteristics and external factors.

Table 2.1 *Summary of human factors that influence a driver's willingness to engage in automated driving*

External factors	Driver processes	Driver characteristics
Environment factors	Trust in automation	Demographic factors
Vehicle automation system	Mental model	Personality
Trip characteristics	Perception of safety/risk	Driver state
	Driving task workload	Attitudes

2.3 Review of factors relevant to the research questions

This section discusses existing research on factors issues identified in the adapted JCTF and presented in **Error! Reference source not found.** and assesses their relevance to the drivers WTE (willingness to engage automated driving mode) or preference of vehicle control mode in a Level 3 automated vehicle. Where possible, findings from the existing literature are used to predict the direction of effects.

2.3.1 External factors

The three most relevant external factors identified by the theoretical framework were: environment, vehicle automation system and trip characteristics.

Environment

From the range of possible environmental factors that are likely to play a role in determining a driver's willingness to engage automated driving, several were identified as suitable for research in a driving simulator. They were road characteristics, traffic density, situation complexity and driving speed. Each of these factors can be manipulated in the simulated environment.

Roads can be characterised by a variety of factors such as width, curvature, speed limit, quality of road markings, quality of surface, visibility, type of surroundings and more. Although it was not possible to find studies that directly established a link between road characteristics and the use of vehicle automation, findings from several studies were able to provide indirect feedback on this relationship. Puga (2016), in a study on willingness to use ACC (adaptive cruise control), identified a positive effect of good road conditions. For example, driving on a straight road was associated with an increased willingness to use ACC. Merat, Jamson, Lai and Carsten (2014) observed an increase in engagement of automated driving on a motorway compared to urban roads. As motorways are generally wider and straighter than urban roads this finding further suggests that road characteristics are important factors in determining driver's WTE. It is therefore expected that factors such as high quality of roads, good conditions, and familiarity with the road would have a positive effect on WTE.

Traffic density is known to have an effect on driving task demands. For example, previous studies such as Baldwin and Coyne (2003), Brookhuis et al. (1991) and De Waard et al. (2008) established that high traffic density is associated with increased driver workload. Several studies reported a link between traffic density and automated driving. Merat, Jamson, Lai and Carsten (2014) identified light traffic conditions as a factor that contributed to the choice of automated driving mode on the motorway. In a survey-based study, Voermans (2015) found the negative effect of high traffic density on willingness to use vehicle automation. In their simulator study, Radlmayr et al. (2014) found a strong negative influence of traffic density on the quality of takeovers during automated driving that may indirectly affect the choice of vehicle control mode. The findings of these studies provide substantial evidence in support of the assumption that the increase in traffic density has a negative effect on WTE.

Many factors can contribute to driving situation complexity, such as saturation of visual scene or visual clutter (traffic lights, signs, road markings, billboards), the behaviour of other road users, weather conditions and more. Review of the literature suggests that the effect of situation complexity is manifested through the difficulty of a driving task. Cantin et al. (2009) and Paxion et al. (2014) found situation complexity to be highly correlated to driving task workload. Similarly, Cabrall and Winter (2017) concluded that the complexity of the driving scene corresponds to the subjective effort, while Stapel et al. (2019) found that perceived and objective workload increased with complexity. With their study findings, Faure et al. (2016) confirmed that drivers' mental workload level increased with the complexity of the driving environment. One of the frequently used examples of increased situation complexity is fog. Fog is recognised as one of the most dangerous conditions for drivers (Saffarian, Happee, et al., 2012). Several studies confirmed that such conditions contributed to the increase in driving task demands. In their simulator study, Jeihani and Banerjee (2018) observed a significant reduction in speed due to the onset of fog, confirming an increase in driving task workload as a result of new road conditions while Hoogendoorn et al. (2011) found that mental workload increased significantly. Several other studies reported the effects of speed on driver workload (Fuller, 2005; M. S. Young & Stanton, 2004). Lustgarten & Le Vine (2017) reported speed as one of the most important factors for the selection of automated driving. Merat and de Waard (2014) observed that driver average speed on the motorway was higher during manual driving compared to automated driving. This suggests that lower driving speed may be associated with higher WTE.

Effects of situation complexity have been investigated for other aspects of driver behaviour in automated vehicles such as automation fallbacks. In their investigation of take-overs, Louw et al. (2017) used different levels of fog to increase task complexity and found that increase in visual demands had a negative effect on take-over performance. Eriksson (2014) found that traffic complexity had an effect on decision-making time within automated driving where an increase in complexity resulted in longer times. Walch et al. (2016) made an assumption that complex and unclear situations create a preference for manual vehicle control.

Despite a lack of research results that could be directly linked to the research question, existing evidence suggests that driver behaviour in Level 3 automated vehicle will be affected by situation complexity. It is likely that an increase in situation complexity would have a negative effect on WTE.

Vehicle automation system

A literature search identified three important factors in relation to the vehicle automation system. They are the design of AV HMI (human-machine interface), automated driving style, and automation malfunctions and failures.

AV HMI Design. There are no current universally-accepted standards for the design of the HMI for automated vehicles although several studies have attempted to produce such guidelines. Debernard, Önen, Chauvin, Pokam, and Langlois (2016) proposed methodologies for the design of such interfaces and attempted to answer what should be displayed, how and when. They suggested that the interface must allow the driver to establish accurate situation awareness during each driving mode as well as during transitions between driving modes. Carsten and Martens (2018) proposed a set of design principles for in-vehicle HMI. The HMI design in automated vehicles should provide a required understanding of the AV capabilities and status, produce correct calibration of trust, stimulate an appropriate level of attention and intervention, minimise automation surprises, offer comfort to the human user and be usable. The importance of HMI in the creation of trust in automated vehicles has been identified in research by Ekman et al (2017). Their recommendations are based on the realisation that the building of trust is a dynamic process that starts before the user experiences the system and continues long after. Therefore, HMI design needs to be more holistic and able to adapt over time. Similarly, Hjälmdahl et al. (2017) concluded that HMI must be trusted and accepted by drivers. It should not overburden the driver, address sleepiness and satisfy legislations. More recently, based on results of their study on effects of exposure to changes in information usage, Ulahannan et al. (2020) made recommendations on the design of adaptive interfaces for partially automated vehicles.

In their study (Koo et al., 2016) demonstrated a strong positive effect of voice alerts as part of HMI in an automated vehicle on the subjective driving experience. Anthropomorphic cues such as name, gender or voice, appear to increase a user's willingness to trust automated vehicle technology in place of humans (Waytz et al., 2014). Hoff and Bashir (2015) too suggested an increase in automorphism, transparency, politeness and ease of use to promote trust in automation and minimise automation disuse.

Creaser and Fitch (2015) concluded that the design of automated vehicle HMI needs to *"facilitate development of a functional mental model that can guide the driver through a variety of vehicle interactions"* (p 86). For example, HMI could address the problem reported by Louw et al. (2015) who observed that drivers experiencing automation are slower in identifying potential collisions and, when identified, collisions are evaded more erratically and at a faster pace. Although not being explicitly investigated in this program, issue of transition of control has been recognised as one of the main challenges (Merat, Jamson, Lai, Daly, et al., 2014) and it is likely to contribute to the perception of HMI. IHRA (2011) provided an example of design principles aiming to address this issue. It can be concluded that the well-designed HMI of an automated vehicle is likely to be positively correlated with willingness to engage automation.

Automated Driving Style. Several studies identified the importance of driving style in the context of acceptance of automated driving. The findings of Karjanto et al. (2016) suggested that driver comfort and the effects of motion sickness will be an important factor in determining acceptable automated driving style. Bellem et al. (2016) investigated safety, functionality and comfort of automated driving style and identified manoeuvre-specific metrics for the development of comfortable automated driving. Siebert et al. (2017) suggested that Level 3 automated vehicles would need to adapt to the individual driver's preferences. Oliveira et al (2018) found that human-like behaviour inspires confidence in automated driving due to familiarity, hence it is not surprising that unpredictable behaviour patterns of AV are likely to make occupants feel uncomfortable (von Sawitzky et al., 2019). In their study, Basu et al. (2017) found that users of automated vehicles preferred a more defensive driving style to their own. Johns et al. (2016) found that a gentler automated driving style was generally more acceptable by drivers. In summary, a more acceptable automated driving style is likely to have a positive effect on WTE.

Automation Malfunctions and Failures. One of the most critical human factors issues in the context of automated driving is the problem of automation failure. Zmud et al. (2016) identified malfunctions or system failures of vehicle automation as the main concern in their survey while Kraus et al. (2019) found that experience of automation fallbacks and failures caused a temporary decrease in trust. Bainbridge (1983) concluded that humans are poor supervisors of automation. Consequently, automation failure in Level 3 can make a driving task more difficult for the driver than manual driving. Strand et al. (2014) concluded that driving performance degrades as a result of an increased level of automation. Similarly, Shen (2016) who investigated the effect of lane-keeping system failures on driver responses, concluded that driver performance was worse with the use of automation. As a countermeasure, Hoff and Bashir (2015) suggested that ongoing feedback on the reliability of automation can facilitate appropriate trust. In the Level 3 automated system, the driver who was previously active in controlling the vehicle becomes an observer by selecting an automated vehicle control mode. As an observer, the driver's new task is to monitor the system and to intervene when something goes wrong or they stop trusting the system. For example, research suggests that having no automation is less frustrating than automation that requires frequent human intervention (de Winter et al., 2013). It can be assumed that this frustration would have a negative effect on WTE. Therefore, both the severity and frequency of automation failures are likely to have a negative effect on a driver's willingness to engage automation.

Trip characteristics

The trip characteristics play an important role in the acceptance of AVs (Becker & Axhausen, 2017). One of the trip characteristics that can be manipulated in simulator studies is distance. Long trip distances are found to induce more driver fatigue and sleep deprivation in drivers (Philip et al., 1999). Sanchez et al. (2012) concluded that trip distance influences driver behaviour, as longer distances are likely to demand more concentration. Voermans (2015) highlighted the importance of trip length, concluding that vehicle automation would be preferred for trips longer than 100 km. Ashkrof et al. (2019) investigated the effect of trip purpose and distance on the stated preference between conventional transport modes and automated transport modes. They found the preference for automated transport for short and long distances. A similar trend has been observed in patterns of use of ACC (adaptive cruise control). Puga (2016) found a positive effect between trip distance and willingness to use ACC as drivers were more willing to use ACC during longer trips. Kyriakidis et al. (2015) found a positive effect of travel distance on willingness to pay for an automated vehicle. Therefore, it is expected that longer driving distances would have a positive effect on WTE.

2.3.2 Driver processes

Driver processes of the JCTF are constructed from a range of interrelated psychological concepts. Consequently, it is not always possible to isolate and discuss a single concept in the context of the overall research question. Therefore, taking into account the operational domain of this research, four key driver process concepts were selected. They are: trust in automation, mental models, perception of safety and driving task workload.

Trust in automation

Trust can be referred to as a belief that another entity will behave with benevolence, competence, integrity and predictability (Mcknight & Chervany, 2000). Lee and See (2004) defined trust as *"the attitude that an agent will help achieve an individual's goals in a situation characterized by uncertainty and vulnerability"* (p. 54). The importance of trust in automation has been well acknowledged in the human factors literature as many studies demonstrated that trust is a major factor in the acceptance of automation (Lee & Moray, 1992; Lee & See, 2004; Parasuraman et al., 2008).

More recent research investigated the role of trust in automation in the context of the adoption of AVs, user acceptance of AVs and intention to use AVs. Körber et al. (2018) stated that *"Trust in automation is a key determinant for the adoption of automated systems and their appropriate use"* (p. 1), other researchers, too, identified trust in technology as one of the key factors to the adoption of automated cars (Hegner et al., 2019; Kaur & Rampersad, 2018; Zoellick et al., 2019b). In their review (Adnan et al., 2018) and study by Molnar et al. (2018), it was concluded that the level of trust in vehicle automation technology was an important factor for user acceptance. Xu et al. (2018) found that trust indirectly affects AV acceptance through other determinants such as willingness to repeat the use of automation and intention to use automation. Choi and Ji (2015) provided evidence that trust is a major determinant of intention to use AVs.

Trust in automation is influenced by a range of factors. The development of the driver's trust in the automated system may depend upon appropriate feedback given by the system (Hoff & Bashir, 2015; Lee & See, 2004; Stanton & Young, 2000). The amount of feedback sought from an automated system by a human operator is directly related to the degree of trust they have in it to perform without failure (Muir & Moray, 1996). Lee and See (2004) proposed increasing transparency of automation algorithms as a method to improve feedback to the driver and increase the level of trust in the system. Hoff and Bashir (2015) suggested that trust can be facilitated by increasing the AV system's anthropomorphism, transparency and ease of use. Exposure to vehicle automation also has a positive influence on trust as reported by Gold et al. (2015) who found that the experience of highly automated driving in a simulator increased self-reported trust in automation and Rudin-Brown and Parker (2004) who reported increased trust in ACC after exposure to the system in their test-track study. Also, the duration of exposure is important because long-term use of an automated system facilitates the building of trust (Muir & Moray, 1996). The importance of training has been highlighted by Payre et al. (2017) with findings that training drivers through practice and explaining its underlying logic, positively influences trust in vehicle automation.

In their study, Lau et al. (2018) emphasised the importance of an appropriate level of driver trust in automation. An appropriate level of trust is critical as inappropriate trust could lead to reduced performance of the overall system (Lee & Moray, 1992) or complacency (Parasuraman & Manzey, 2010). Automation complacency results in a poorer detection of system malfunctions under automation compared with under manual control with automated highway driving being particularly susceptible to complacency (de Waard & Van der Hulst, 1999). Lack of trust would potentially lead to misuse of the system (Muir, 1994), while on the other hand, overtrust in systems that are commonly reliable but prone to rare, unpredictable, and hazardous failures can present a significant danger. Dickie (2010) showed that overtrust in ACC corresponds to hazardous use of ACC and lack of awareness regarding limitations of the system. Wintersberger and Riener (2016) concluded that trust issues need to be resolved and demonstrated before the benefits of vehicle automation could be achieved. The subjective trust must match objective (appropriate) trust to prevent misuse of vehicle automation. This can be achieved by training on how to accept and use these systems.

Although no studies have specifically investigated driver's WTE vehicle automation, it is possible to make indirect conclusions of the effect on trust on WTE based on exiting research. For example, Choi and Ji

(2015) found a strong positive effect on the intention to adopt AVs while Liu, Yang, et al. (2019) found trust to be a steady predictor for acceptance of AVs. It is therefore assumed that higher levels of trust in automation will have a positive effect on WTE.

Perception of safety/Perception of risk

Perception of safety (POS) or perception of risk (these terms are used interchangeably) have previously been investigated in relation to driver behaviour. The findings from relevant literature suggest that drivers' perception of safety has an important effect on their behaviour (Wang et al., 2002). Similarly, Näätänen and Summala (1974) stated that drivers' subjective perception of risk is *"an important determinant of their decisions"* (p. 11). In their study, Wang et al. (2011) concluded that the driver's subjective perception of road safety has an important impact on traffic safety. They stated that if the subjective judgement of safety is higher than the actual road safety resulting in an increased risk of crashes. The study identified several factors that affect POS: driver factors, road factors, vehicle factors and environmental factors.

The existing literature shows that the effects of these factors have been investigated. Fildes et al. (1989) concluded that reduced perception of safety may be correlated to a reduction in driving speed. Tanida et al. (2018) found the link between perceived safety and anticipatory control in everyday driving. They also identified a sense of personal control as one of the factors. A higher risk is perceived if the situation is not under personal control (Brun, 1994). Risk perception in driving also depends on the driver's experience (Kinnear et al., 2013). Thomas and Walton (2008) found that perception of safety is increased in larger vehicles such as SUV, fuelled by the public perception that larger vehicle mass offers better personal protection. Fuller et al. (2008) concluded that feelings of risk may help to prevent engagement in tasks that are too difficult.

Drivers' level of perceived risk may change due to the presence of driving assistance systems (Rajaonah et al., 2008). Haupt and Risser (2013) warned of possible negative effects of ADAS suggesting that it may increase the feeling of safety and facilitate engagement in non-driving tasks. Previous research has shown that drivers, when feeling safe, often divert their attention from driving to non-driving tasks (Carroll et al., 2002); therefore, subjective perception of safety may be susceptible to exposure to automated driving. For example, Skottke et al. (2014) demonstrated a change in drivers' perception of safe headway when switching to manual control after driving in a platoon of AVs.

The existing literature failed to provide a clear link between the perception of safety (perception of risk) and WTE. Ernst and Reinelt (2017) found an indirect positive influence of perceived traffic safety on acceptance of AVs. Choi and Ji (2015) did not find perceived risk to be a significant predictor of behaviour in AVs. They, however, found that trust in automation reduced perceived risk. The association between risk and trust was also highlighted by Lee and Kolodge (2018) in the context of acceptance of AVs. Zoellick et al. (2019) identified perceived safety as one of the strong predictors of intention to use AVs. Puga (2016) too, identified safety as one of the factors that underlie the use of ACC. These studies suggest that perception of safety has a positive effect on WTE.

Mental models

A mental model is "internal representations containing meaningful declarative and procedural knowledge that people use to understand specific phenomena" (Al-Diban, 2012, p. 2200). It is a representation of road situations, usually developed together with other driving skills. In the context of the automated driving mental model refers to a driver's knowledge of what automation can and can not do. A mental model is developed through education, training and exposure. For example, Lin et al. (2018) concluded that after two weeks drivers had an accurate mental model and were able to identify safe usage conditions of Tesla Autopilot. Similarly, experiences with ADAS and awareness of technological limits are associated with positive attitudes towards vehicle automation (Beggiato & Krems, 2013; Crump et al., 2016; Xiong et al., 2012).

An incorrect mental model presents a risk, especially at Level 3 automated driving as drivers are required to act as supervisors of the automated system. Creaser and Fitch (2015) observed that the development of a mental model is often incomplete and may result in a driver's inability to adequately respond to problematic situations. In response to this issue, Merat, Jamson, Lai and Carsten (2014) emphasised the need to inform drivers about the limitations of the system and scenarios regarding the possible failures of automation. Bianchi Piccinini et al. (2013) found the improper mental model to be one of the causes of negative behavioural adaptation. In their model of driver behaviour in a vehicle equipped with ACC, Boer and Hoedemaeker (1998) concluded that drivers rely on the mental model when deciding whether to drive manually or activate automation. It is therefore likely that an accurate mental model is positively correlated to WTE.

Driving task workload

Driving task workload can be perceived as the demands presented to the driver (De Waard, 1996) while driving task difficulty is the difference between driver capability and driving task demands (Fuller & Santos, 2002). Three subcategories of driving task workload: visual, motor (manual) and mental (cognitive) are identified and usually studied (Hoedemaeker, 2002; Zhang et al., 2004). Fuller et al. (2008) identified features of the road environment, presence and behaviour of other road users, features of the vehicle being driven and the speed of travel as factors that constitute driving task demands. During (manual) driving, the driver needs to allocate the resources required for the driving, to maintain this capability above driving task demands (Fuller, 2005). Brookhuis and de Waard (2010) concluded that for adequate driving performance, driving task workload should not be too high or too low. Therefore, use of automation may have benefits under high workload conditions to assist driver in cases where they could be otherwise overloaded.

The use of ADAS has been shown to affect the driving task workload. Hjälmdahl et al. (2017) measured driver workload and found that it was higher for partial than for full automation. It is therefore not surprising that one of the main reasons for use of ADAS is the ease of driving as concluded by Strand et al. (2011) who explored end-user experiences with ACC and implications on safety. However, de Winter et al. (2014) concluded that highly automated driving has a possibility to divert attention to non-driving tasks, suggesting a reduction in driving task workload as a result of automation utilisation. This claim is supported by Rudin-Brown and Parker (2004) who investigated the behavioural adaptation of drivers as a result of ACC use and by (Morando, 2017). They concluded that the drivers, given the reduction in workload when using ACC may be tempted to engage in other activities when driving. This diversion of attention may lead to excessive reliance on automated systems and avoidance of certain activities such as overtaking (Jamson et al., 2011). Carsten et al. (2013) also confirmed that engagement in non-driving tasks increased with the level of automation. Based on the evidence from the literature (Stanton et al., 1997; Strand et al., 2014) it can be concluded that the use of ADAS reduces driving task workload except for fallback situations.

In conclusion, previous research measured driver workload at different levels of vehicle automation, while this research investigates the effect of driving task workload on WTE. Since JCTF represents driver processes as a complex interplay it is difficult to isolate the effects of driving task workload from other processes and uniformly predict the direction of the effect on WTE without consideration of other relevant factors. However, it is expected that an increase in driving task workload would have a significant effect on WTE. For this exercise, the predicted direction of the effect is assumed to be negative.

2.3.3 Driver characteristics

Demographic factors

It is expected that driver characteristics play an important role in determining whether to use automated driving or not. Several surveys (Giffi et al., 2014; König & Neumayr, 2017) confirmed these predictions. For example, older drivers expressed more concerns about automated driving than younger drivers and females expressed more concerns than males. Demographic factors discussed were age, driving experience and gender.

The effects of aging and driving experience on road safety are well documented. For example, young drivers are more likely to lack hazard perception skills (Borowsky et al., 2010) and situational awareness (Wright et al., 2016) than experienced drivers, while aging-related conditions affect the mental and physical capacity of a driver (Ball & Rebok, 1994; Cantin et al., 2009). Molnar et al. (2017) found that older drivers are likely to find a transfer of control more challenging. The effects of age were often analysed in surveys on automated vehicles. Kyriakidis et al. (2015) found that early adopters of automated vehicles will be young and those who spend more time in vehicles. In a study by a global market research company (J.D. Power, 2016), the findings indicate that younger individuals may be more willing to ride in autonomous vehicles than older individuals. Hulse et al. (2018) found that *"younger participants were more often accepting automated cars and less opposing them than older participants"* (p 8). Zoellick et al. (2019) found that older drivers are less intent to use AVs. Although being a significant predictor of intention to use AVs, they observed uncertainty and confusion concerning the effect of age and gender on other constructs (trust in AV and perceived safety). Rödel et al. (2014) identified an effect of the degree of autonomy on a view of vehicle automation finding that older drivers prefer a higher level of automation.

There is strong evidence showing that experience with automation has a strong effect on how different age groups perceive it. In a study by Gold et al. (2015) elderly drivers exhibited higher trust in automation than younger drivers after experiencing highly automated driving in a simulator. A similar observation was reported by Crump et al. (2016) who found that the difference in opinion about ADAS between older and younger groups was dependent on experience with such technology. Older drivers rated ADAS more favourably than younger after exposure. The strong positive effect of familiarity with AVs among older drivers is also reported by Rahman et al. (2019).

The main effect of driving experience is the development of a driver's abilities to perform the driving task. Rudin-Brown et al. (2014) observed a positive effect of driving experience on drivers' ability to assess the road environment and adapt their behaviour to improve safety. Kinnear et al. (2013) identified a critical role of driving experience in recognising developing hazards. Therefore, more experienced drivers might be less willing to trust an automated system due to perceived loss of control (Rödel et al., 2014) when considering the engagement of automated control mode.

Multiple survey results suggest that males might be more are more likely to accept AVs than females (Böhm et al., 2017; Hulse et al., 2018; Liljamo et al., 2018). Hohenberger et al. (2016) observed differences in willingness to use automated cars between males and females in their survey study with females showing lower usage intentions. A similar observation was made by Hardman et al. (2019). However, there are also somewhat conflicting reports such as Johns et al. (2016) who observed that female participants in comparison to males, exhibited a higher level of trust in automation, better communicated with automation and remained more engaged during the drive. Dickie (2010) found a difference between genders in a study on ACC, with males being more prone to overtrust in ACC due to possibly more positive attitudes. Smith and Anderson (2017) research found that in the United States, interest in using the automated vehicle was higher in males than in females, in under the age of 50 than older, among higher educated and among urban area residents.

In conclusion, based on the available literature, it is likely that age and driving experience have a negative effect on WTE, while being a male has a positive effect on WTE.

Personality

The JCTF identifies several personality factors that may affect WTE such as driving enjoyment, locus of control and driving confidence. In the context of the current discussion, driving enjoyment is referred to as the pleasure that the driver derives from being in the control of the vehicle, as experienced during manual driving. Ernst and Reinelt (2017) identified the negative influence of driving enjoyment on AV acceptance using online questionnaires. In the investigation of Tesla Autopilot users (Hardman et al., 2019) driving enjoyment was found to be negatively associated with Autopilot use. Eckoldt et al. (2012) showed that ACC negatively impacts driving enjoyment because of the removed driver's connection with the car which is an important component of pleasure that the driver derives from driving. Hegner et al. (2019) emphasised the negative effect of driving enjoyment in relation to AV adoption. In their survey, Rödel et al. (2014) reported a decrease in perceived enjoyment when the level of vehicle automation is increased.

Seel (2012) refers to locus of control as *"the extent to which individuals believe that they can control events that affect them"* (p118). A high internal locus of control correlates to one's belief that events are the result of own actions while a person with an external locus of control believes that events are the result of environmental reasons (Stanton & Young, 2000). Choi and Ji (2015) found a significant effect of external locus of control on behaviour in automated vehicles. In their experiments on behaviour adaptation to a lane departure warning system, Rudin-Brown and Noy (2002) observed external locus of control participants to report higher trust in the system.

Popken et al. (2015) investigated a driver's willingness to allocate control to a lane-keeping assistance system as a function of the level of assistance. The simulator study compared three levels of assistance (without lane-keeping assistance, lane departure warning system as low level and lane-keeping control as high assistance). They found that drivers who regarded themselves as anxious and unconfident drivers placed more trust in the lane-keeping control system. Indirect support to this finding is provided by Arakawa et al. (2018) who observed that drivers reliant on automated driving experience stress when taking over control in the case of automation failure. In conclusion, it is likely that level of personal driving enjoyment, internal locus of control and driving confidence will have a negative effect on WTE.

Driver state

Driver state refers to acute physical and mental conditions that may affect driving performance such as fatigue and motion sickness. Neubauer et al. (2012) found in their study that fatigued drivers were more likely to use automation. Similarly, Puga (2016) identified fatigue as one of the factors that contributed to their willingness to use ACC. However, driving in an automated mode can also contribute to fatigue. For example, Jamson et al. (2013) observed increased symptoms of fatigue with vehicle automation. Hjälmdahl et al. (2017) tested the sleepiness of truck drivers during three automation levels (no automation, partial automation and full automation) observing that automated driving increased the level of sleepiness. This suggests that fatigued drivers are likely to be less willing to resume manual control of the vehicle. In a study that investigated vehicle control takeover, Jarosch et al. (2019) confirmed the negative effect of fatigue on takeover (fallback) performance. They used a non-driving task to induce fatigue during long drives in conditional automation. A similar finding was reported by Feldhutter et al. (2018). Such experiences may negatively associate fatigue and willingness to engage automation. Driver state can be affected by congnitive load created by engagement in non-driving tasks during automated driving. Melnicuk et al. (2021) found that a higher level of cognitive load during automated driving results in a longer time required to stabilise manual driving.

Motion sickness or self-driving carsickness (Nordhoff et al., 2016) will be a very relevant factor for user acceptance of AVs. As a result of engagement in the non-driving task, a sensory conflict is created. This issue has been frequently overlooked; however, as users of AVs are expected to engage in non-driving activities it is likely to become a more significant problem and negatively affect the willingness to engage automated driving. The magnitude of this issue is likely to depend on the success of technological solutions intended to prevent carsickness. Countermeasures are proposed, such as Ihemedu-Steinke et al. (2018) who suggested the implementation of split-screen technology to present information about movement and minimise the occurrence of motion sickness and Smyth et al. (2021) who developed a visuospatial training tool for reduction of motion sickness. Based on the relevant literature it is likely that fatigue has a positive effect on WTE while motion sickness has a negative effect on WTE.

Attitudes towards technology

Attitudes towards technology and more specifically attitudes towards automated driving are often developed in society (Haupt & Risser, 2013) and by media influence (Feldhütter et al., 2016a). Positive attitudes towards technology may be indicated by being an early adopter, having trust in technology or being willing to pay for new technology. The study of attitudes and concerns on AVs by Liljamo et al. (2018) indicated a strong link between attitudes towards new technology and adoption of the technology. Surveys also show that attitudes towards AV are based on previous experiences with technology such as computer systems (Lee & Kolodge, 2018).

Several studies identified driver attitude as a predictor for AV acceptance (Böhm et al., 2017; Zoellick et al., 2019b). Such findings are confirmed in a study of Tesla Autopilot (Hardman et al., 2019), which identified positive attitudes towards technology correlate with increased Tesla Autopilot use. Based on the above sources, it is probable that positive attitudes towards technology will have a positive effect on WTE.

2.4 Summary and conclusions

This chapter presented a brief overview of research methodologies in human factors of automated driving, identified a theoretical framework for the investigation of drivers' willingness to engage automated driving (WTE) in a Level 3 automated vehicle in everyday driving situations and a review of relevant human factors issues. Unlike previous research that explored driver willingness in the context of automated driving, such as willingness to pay and willingness to use automated vehicles, WTE was being observed in real-time, with drivers giving their ratings as the driving situation changes.

The theoretical framework, JCTF, was adapted to focus on driver processes that control WTE resulting in the identification of factors relevant to the research question. Due to the inherent complexity of interactions between factors as presented in JCTF, the effect of each factor is assessed in isolation, where possible. **Figure 2.6** presents a summary of the factors considered to be relevant to the driver's WTE in Level 3 AV. Based on the research evidence presented above, the likely direction of effect for each factor is illustrated with colour: the green colour indicates a positive effect, while the peach colour indicates a negative effect.

It is concluded that the development of an accurate model that can predict a driver's WTE (WTRC) is difficult at this evolutionary stage of vehicle automation as interactions between the many factors and processes are complex while there are ongoing technological developments taking place and access to real automated vehicles is limited. Findings will be used in the course of this research program to formulate any additional hypotheses relevant to the individual research studies in addition to the main hypotheses stated in Chapter 1, and a guide for the design of experiments and developing experimental protocols.

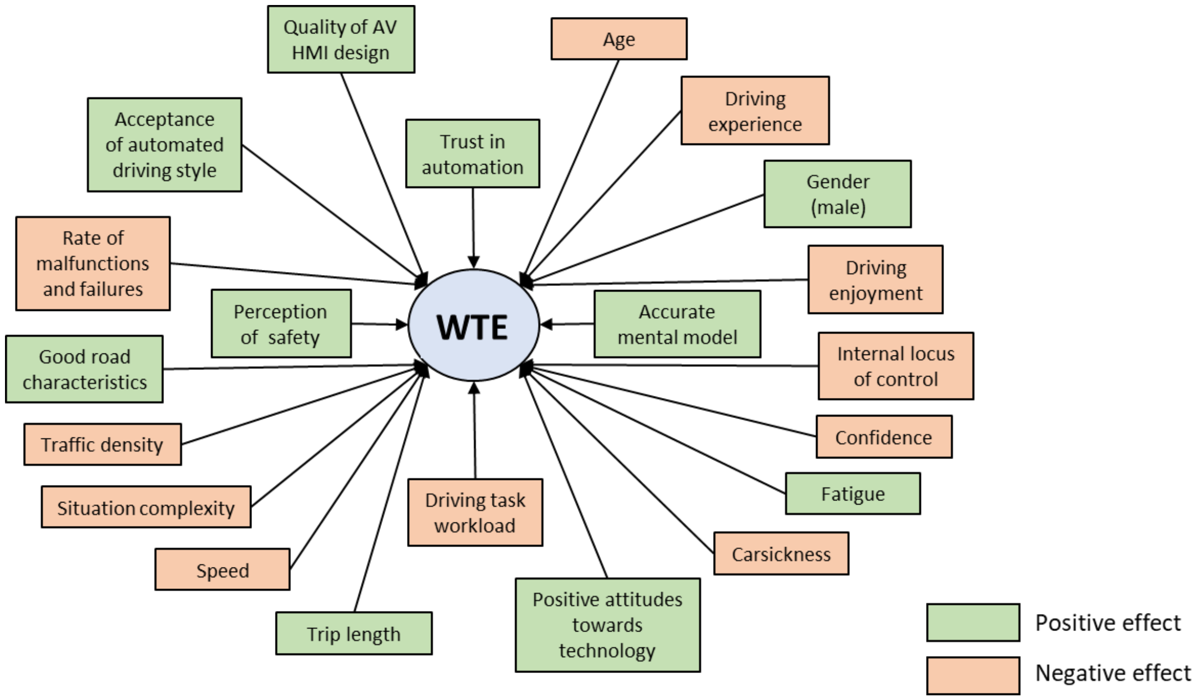


Figure 2.6 *Summary of factors that are likely to influence WTE in Level 3 AV*

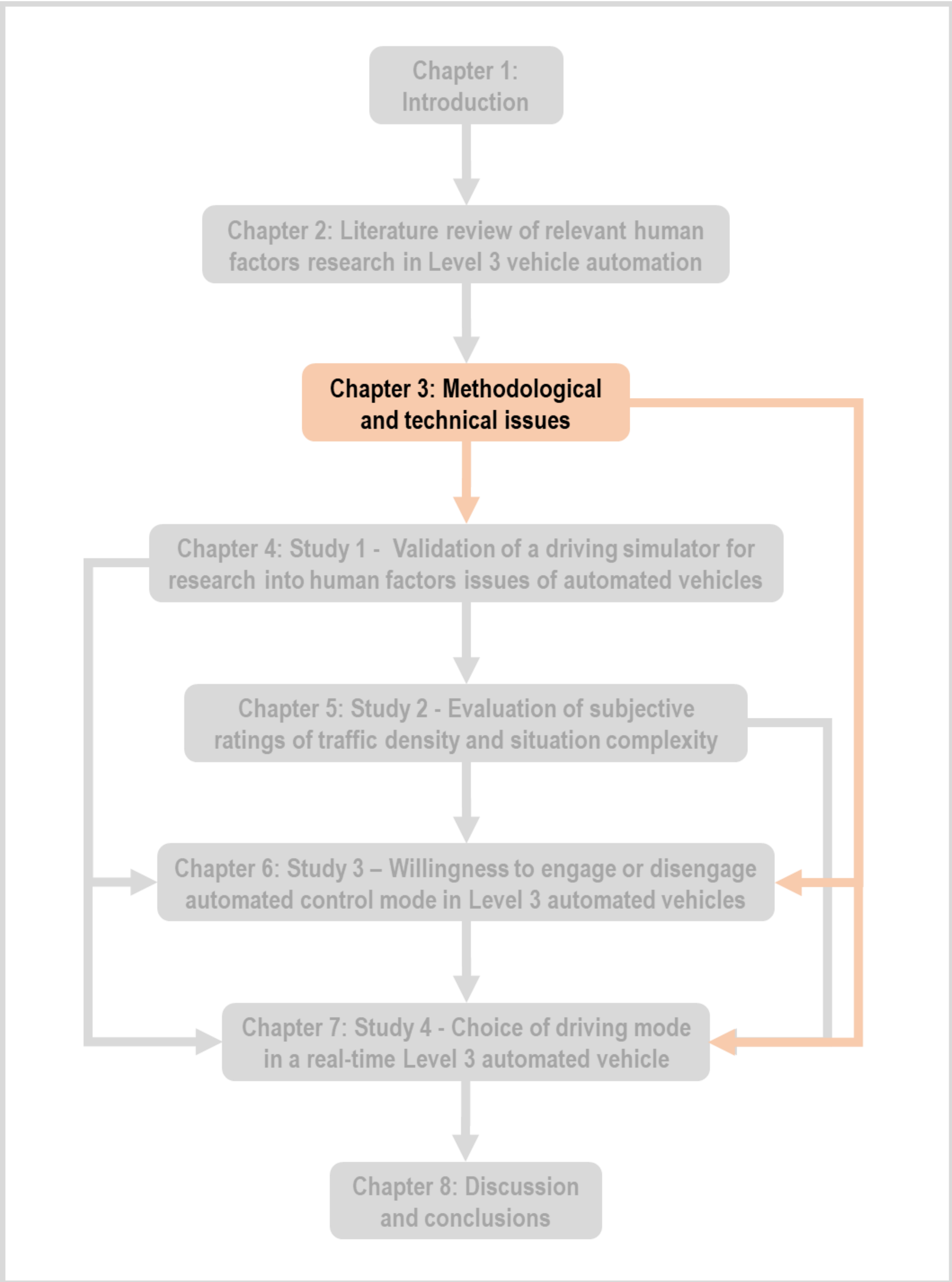
Table 2.2 presents a list of hypotheses derived from the literature review that will be tested in this research. These hypotheses address the overall research questions presented in Chapter 1. Given the lack of relevant research that specifically addresses WTE in Level 3 automated vehicles, some of the evidence used to justify these hypotheses relates to level 2 automation. The last hypothesis from **Table 2.2** addresses the secondary research question stated in Chapter 1, the validity of the simulator for conducting human factors research into vehicle automation.

Table 2.2 *List of hypotheses to be tested in this research*

#	Factor	Hypothesis
1	Traffic density	High traffic density has a negative effect on WTE
2	Situation complexity	High situation complexity has a negative effect on WTE
3	Driving speed	Higher driving speed has a negative effect on WTE
4	Driver age	Increase in driver age has a negative effect on WTE
5	Driving experience	Increase in driving experience has a negative effect on WTE
6	Gender	Being a male driver has a positive effect on WTE
7	Driving enjoyment	High level of driving enjoyment has a negative effect on WTE
8	Driver confidence	High driver confidence has a negative effect on WTE
9	Attitudes towards technology	Positive attitudes towards technology have a positive effect on WTE
10	Trust in automation	High trust in automation has a positive effect on WTE
11	Perception of safety	High perception of safety has a positive effect on WTE
12	Validity of driving simulator	MUARC Automation driving simulator is a valid tool for research of human factors issues in automated driving

These hypotheses will be tested in the following chapters through four individual studies. However, before that, there were several technical and methodological issues to be addressed in order to carry out these studies. They are discussed and explained in Chapter 3.

CHAPTER 3


Chapter 1: Introduction
Chapter 2: Literature review of relevant human factors research in Level 3 vehicle automation
Chapter 3: Methodological and technical issues
Chapter 4: Study 1 - Validation of a driving simulator for research into human factors issues of automated vehicles
Chapter 5: Study 2 - Evaluation of subjective ratings of traffic density and situation complexity
Chapter 6: Study 3 – Willingness to engage or disengage automated control mode in Level 3 automated vehicles
Chapter 7: Study 4 - Choice of driving mode in a real-time Level 3 automated vehicle
Chapter 8: Discussion and conclusions

Chapter 3 Methodological and Technical issues

3.1 Introduction

This chapter documents work undertaken on a range of technical and methodological problems that needed to be resolved to facilitate the investigation of research questions outlined in the previous chapter. This chapter does not present the actual research work. The rationale for having these issues compiled in a single chapter was to allow the reader to focus on the research studies in Chapters 4 to 7, without being distracted with discussion about technical issues. Activities are presented in chronological order, starting from preparations for the simulator validation study (Study 1) to the final study (Study 4) in this research. The logical and chronological placement of these activities, related to research studies are illustrated in **Figure 1.2** from Chapter 1.

Espié, Gauriat and Duraz (2005) call each research simulator a unique prototype since there is no defined certification for driving simulators or for simulator experiments. It is most often the responsibility of the end-user to develop various solutions for ongoing research demands. At the beginning of this research project, technical requirements for research into the human factors of automated driving exceeded the functionality offered by the existing driving simulators at the Monash University Accident Research Centre. The critical issue was the lack of an automated driving facility, both in terms of software functionality and physical HMI (human-machine interface). Therefore, it was necessary to derive technical solutions during each step of the planned research program. Every such solution allowed the development of simulator scenarios that addressed the current set of research questions. This chapter documents the steps taken ahead of each simulator-based study leading towards the development of true, real-time, interactive automated driving in the simulator.

3.2 Automation driving simulator

3.2.1 Simulator overview

An automation driving simulator was created by the candidate for use in the research program. The Automation driving simulator is based on EcaFaros v7.1 software (ECAGroup, n.d.). This is a commercially produced training simulator application that also allows the development of custom scenarios. This software can be integrated with an external vehicle model such as CarSim by Mechanical Simulation (*CarSim Overview*, n.d.), various HMI peripherals and a motion base system.

The EcaFAROS v7.1 software was installed on a PC with a dedicated 3D graphics card (nVidia GeForce GTX 970). The graphics card supports up to 4 HDMI displays. For current research 3 displays were used. The display system consisted of 46” bezel-less monitors mounted on a static frame that partially surrounded the driver. The field of view was configured to cover 140° horizontally and 37.5° vertically. The sound was delivered by a 5.1 surround speaker system.

The motion and vibrations were provided via a D-Box 250i motion base system (D-BOX, n.d.). A rigid platform was built and mounted on three linear motion actuators. Each linear actuator had a lifting capacity of 114 kg and maximum travel of 35mm. The maximum actuator velocity was 100mm/s and the maximum acceleration was 9.81m/s^2. Actuators had an operating frequency range from 0 to 100 Hz. The placement of actuators (**Figure 3.1**) allowed 2.3° of pitch and 2.9° of the roll without affecting the stability of the whole setup. A dashboard, adjustable car seat including seatbelt sat atop of the platform. The car seat was fully adjustable (distance and backrest angle). It also included a seat belt. The placement of the seat was aligned with actuators to provide optimum loading capacity by distributing weight equally between all three actuators. The maximum weight capacity of the motion base was estimated at 200kg. Additional seats (each with its motion base) could be added to the simulator if required. The latency of visual and motion systems in response to steering wheel input was less than 50 milliseconds.

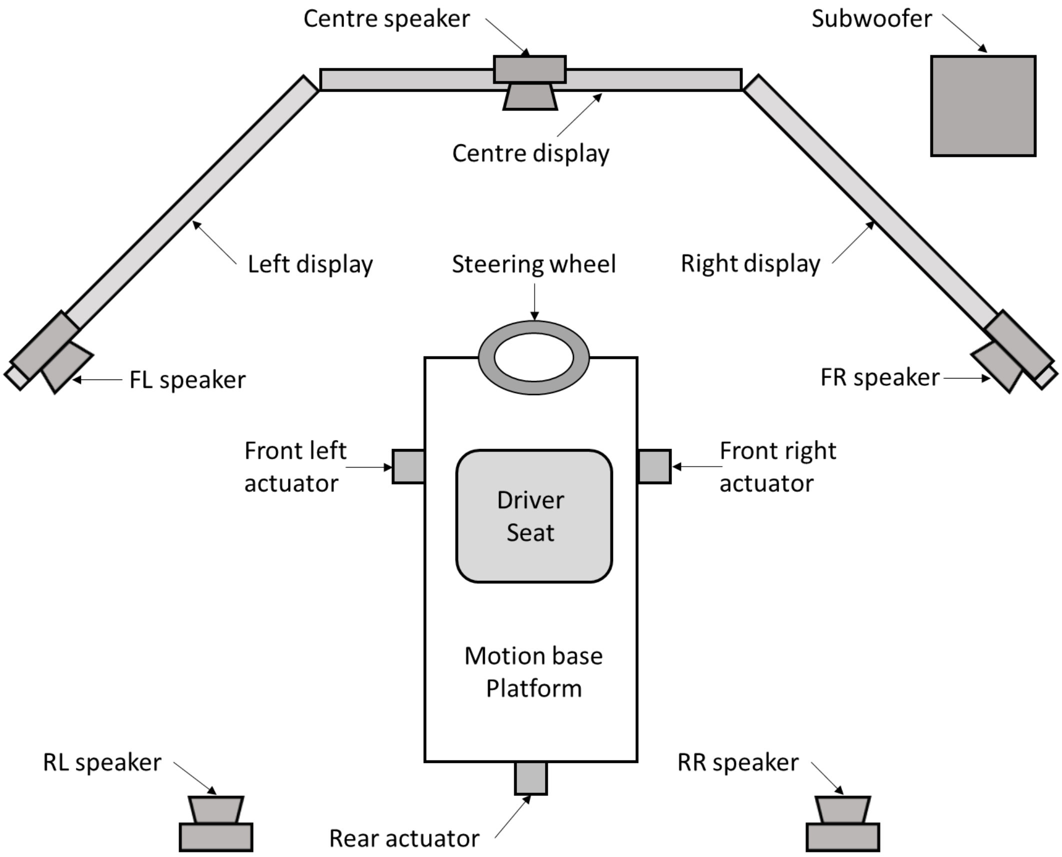


Figure 3.1 *Physical configuration of the automation simulator (top view)*

3.2.2 Lack of automated driving mode

The ECAFaros v7.1 software allowed the creation of custom scenarios that include both virtual environment and active objects. The behaviour of all active objects could be accurately controlled using a GUI (graphical user interface) or scripting language for more complex situations. Despite offering great flexibility in the design of scenarios, the existing version of driving simulator software was not able to represent realistic automated driving. A preview of the driving scenario was possible in a very rudimental form. The purpose of this functionality was not associated with automated driving, it was originally developed for testing simulator scenarios without the need for the scenario developer to physically drive through it. Once this function was activated, the simulator car would rigidly maintain speed and follow the road layout. As a result, lateral and longitudinal movements of the simulator vehicle and visual scene were unrealistic and violent. In addition to this issue, gear changes in the automated driving mode were unrealistically frequent and noisy. Even though the motion base could be controlled or even switched off, visual movements were embedded into the simulator software graphics engine. Therefore, the use of preview functionality was not practical for experimental scenarios. Also, it is highly likely that prolonged exposure to such conditions would induce motion (simulator) sickness.

The following sections in this Chapter chronologically document activities undertaken to overcome the lack of automated driving mode in the simulator and on-road vehicle. Section 3.3 discusses the representation of automated driving in both on-road vehicle and the driving simulator required for Study 1 attempting to validate the driving simulator for specific behavioural aspects. Section 3.4 discusses a technical solution to the representation of automated driving for Study 3. Since a true real-time automated driving (where participants can engage or disengage automation) was not critical for the experimental task automated driving was presented using playback mode. A small pilot study that tested whether tactile transducers could produce vibrations that resembled actual motion base vibrations is described in this section. Finally, Section 3.5 documents the development of an interactive real-time automated driving in the simulator required for Study 4.

3.3 Representation of automated driving for Study 1 (simulator validation)

The first study undertaken in this research project was the validation of the driving simulator. For the driving simulator to be used for specific research, it needs to be validated against real-world conditions. In a well-validated study, there is close agreement between simulator data and data from the real world. Therefore, if the driving simulator is going to be used in the research of the human factors of automated driving it needs to demonstrate a good degree of behavioural validity. This is done by comparing data collected in real-world driving with data collected in the driving simulator.

3.3.1 Representation of Level 3 automation in a real-world vehicle

The main technical challenge to the simulator validation study was the lack of a real Level 3 automated vehicle. The three options considered to represent Level 3 automated driving were a Wizard-of-Oz approach (where the participant believes that a computer controls the car), using a left-hand drive vehicle (with pedestrian seated in the passenger seat on the right side) and using normal right-hand drive vehicle with the participant seated in the right seat. These options were considered and weighted in terms of control, face validity, feasibility and available budget. Due to safety and ethics approval issues, it was decided that a human driver had to play the role of an automated system.

The Wizard-of-Oz approach would be ideal due to the best representation of realistic automated driving conditions. The early implementations of the Wizard-of-Oz technique are described in the report by Green and Wei-Haas (1985). This technique is applicable in all fields of research that involves human-computer interaction and has already been suggested for on-road automated driving research (P. Wang et al., 2017). For example, Walch et al. (2016) used this technique to represent speech recognition of an AV user interface while Johns et al. (2016) used it in the simulator for exploration of shared control in automated driving. One of the requirements of this approach is that the participant should not be aware that a human is controlling the vehicle instead of a computer. Therefore, a parallel set of vehicle controls would have to be implemented and hidden from the view of the participant who is sitting in the driver seat. The development of such controls would be challenging and costly. All modifications to the vehicle would need to comply with the Australian Design Rules (ADR, 2018). In addition, all safety aspects of this approach would have to be approved by the Monash University Human Research Ethics Committee (MUHREC). This evaluation was likely to take longer time than for a more traditional and simpler on-road study application.

Due to the challenges of this methodological solution, the outcome of the application could not be predicted. Therefore, because of the high cost, long development time and unpredictable outcomes of the ethics application and ADR evaluation, this option was not further considered.

The Left-Hand Drive (LHD) approach was more feasible. The participant would be seated in the driver seat of a Right-Hand Drive (RHD) vehicle and would have the correct visual perspective for Australian driving conditions. The disadvantages were a scarcity of LHD vehicles and the cost of hire. The vehicle would need to be hired for at least a month. Also, the outcome of the ethics application would be less certain because of risks associated with the unnatural seating position of the real driver. Therefore, the RHD approach was selected for the simulator validation study. The correct seating position of the participant was the only advantage of the LHD approach, while the RHD approach had a much lower cost (existing MUARC instrumented car) and faster ethics approval. Under such a scenario, the researcher played the role of an automated system. The participant was placed in the passenger seat of the car and instructed to assume that he or she was in Level 3 automated car and could take over manual control if required.

3.3.2 Replication of Level 3 automation in the simulator

After the methodology for the on-road component of the validation study was determined, the same conditions had to be replicated in the driving simulator. This meant that two seats were required and that the researcher had to control the car representing the automation (**Figure 3.2**). Similarly, the participant had to be seated in a passenger seat and instructed to assume that he or she was in a Level 3 automated car and could take over manual control at any time.

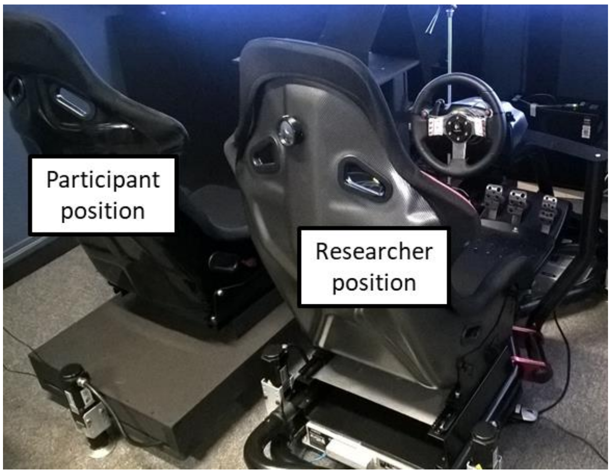


Figure 3.2 *Simulator seating positions*

This was achieved by adding another seat with a control interface on the right side of the simulator. The second seat was mounted on its motion base. Both seats moved in unison driven by the vehicle model calculations. The virtual speedometer was obscured from the participant's view because they were not able to observe speed in the on-road vehicle. As a result, the experimental conditions were kept similar.

3.4 Representation of automated driving for Study 3

3.4.1 Introduction

The main simulator requirement in Study 3 was to expose participants to both manual driving and automated driving conditions. Changes to the vehicle control mode during drives were not required by the experimental task. In the manual driving condition, participant were asked to control the car while in the automated driving condition the automated system controlled the car. As the real-time automated driving functionality was not available two options were considered. The first option was the development of functional automated driving mode, while the second option explored the utilisation of a scenario playback function of the EcaFaros v.7.1 software. Following the advice from simulator software developers, the option of using a replay function was selected. The software developers did not have any additional updates, nor could they offer assistance with the development of the automated driving function at the time, but acknowledged the complexity of such a task.

In the scenario playback mode, a previously recorded simulator drive can be played an unlimited number of times. The playback represents an accurate visual and audio replication of the original drive. Therefore, an experimental drive can be pre-recorded with the researcher driving in manual control mode and presented as an automated drive to each participant during the experimental session.

There were two technical limitations associated with using playback mode as the representation of automated driving. Firstly, there was no option of switching to manual mode or making any input to vehicle controls during the playback. Secondly, the motion base was not supported in the replay mode.

The first limitation was addressed with the study design as participants were asked to complete experimental drives as entirely manual drive and entirely automated drive without changing vehicle control modes. There were two options for addressing the second limitation. The motion base could be disabled in real-time drives therefore making conditions similar to playback drives. Alternatively, a motion base could be substituted with a different system that was supported in both real-time and playback conditions. As discussed in Chapter 2, the motion base was considered important for the simulation of automated driving since it provides haptic cues. These cues may help to keep the driver in the loop during automated driving while being engaged in non-driving activities, particularly in Level 3 automation. Therefore, it was decided to substitute the motion base with tactile transducers capable of providing certain haptic feedback.

3.4.2 Implementation of tactile transducers

Tactile transducers (also known as “shakers”) are devices similar to a common loudspeaker without the cone. Therefore, they are producing only vibrations without sound when rigidly coupled to the hard surface of another object. They are commonly used in home theatres, video gaming chairs, gaming controllers and amusement park rides.

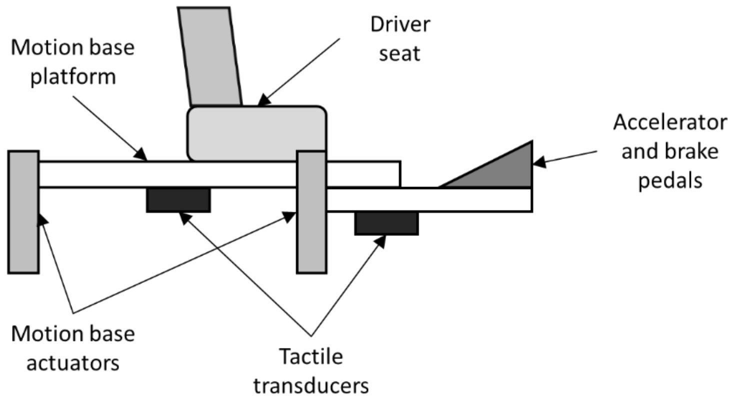


Figure 3.3 *Placement of tactile transducers (side view)*

Two generic tactile transducers were fixated to the motion base platform from underneath (**Figure 3.3**). They were driven by the low-frequency (LF) signal component of the simulator audio output. This signal was fed to a two-channel audio amplifier that powered transducers. The level of vibration was adjusted with a combination of output volume from the simulator and amplifier volume. The balance of vibration between the seat and steering wheel was adjusted with left/right control on the amplifier. The connection between simulator PC and transducers is illustrated in **Figure 3.4**.

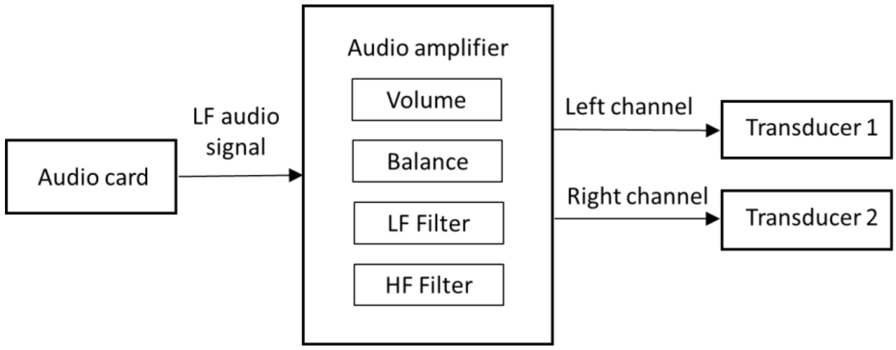


Figure 3.4 *Connection schematic of tactile transducers*

3.4.3 Motion base exploratory study

Method

Following the installation and configuration of tactile transducers, a small exploratory study was conducted to contrast and compare the subjective effects of the two motion base configurations on driving in the simulator. Despite the lack of automated driving mode within the simulator software it was possible to briefly demonstrate automated driving on straight sections of the road by restricting self-driving function to only occasional corrections of steering while implementing a simplistic accelerator pedal feedback to avoid strong vehicle pitch and roll movements. Driving on straight sections did not require frequent steering wheel adjustments but could not be sustained for more than 60 seconds. An additional difficulty was presented at intersections where the steering algorithm struggled to maintain a straight trajectory.

The study design involved driving the same set of five short scenarios under two conditions presented in a counterbalanced order. The first condition represented a real-time simulation of automated driving. The motion base was active, producing pitch, roll and vibration. Tactile transducers were inactive. The second condition represented automated driving in the form of a replayed drive. Under this condition, tactile transducers were producing vibrations while the motion base was inactive. The five short scenarios lasted up to 60 seconds each. They were:

1. Pedestrian near stopped car: The simulator car passed a pedestrian who was standing in front of the stopped car on the left side of the road.
2. Oncoming car: An oncoming car was encountered coming from the opposite side.
3. High traffic density: During the scenario, 10 cars were encountered ahead of the simulator car as well as oncoming cars.
4. Turning truck: A truck turned from the side road onto the main road blocking the way of the simulator car.
5. Empty road: No traffic was present.

Five participants completed the pilot study, three females and two males with an average age of 40.2 (SD = 8.45) years. Each participant drove a total of 10 short drives. At the predetermined point of each drive, the simulation would pause and the participant was asked to give ratings for Willingness to resume manual control of the vehicle and ratings of subjective perception of safety. The method and design of the questionnaire were identical to the method used in Study 1 (see section 4.2). At the end of the session, participants were informed about two different experimental conditions, motion base vs tactile transducer, and asked to identify conditions for two sets of drives.

Results

Data were analysed with Generalising Estimating Equations (GEE) tests for both WTRC (willingness to resume control) and POS (perception of safety). Mean values for POS across all participants for each event are shown in **Figure 3.5**, while scores of WTRC for each event are illustrated as means across all participants in **Figure 3.6**. To allow calculation of mean WTRC, each rating category was given a value: 1 for very willing, 2 for willing, 3 for unwilling and 4 for very unwilling.

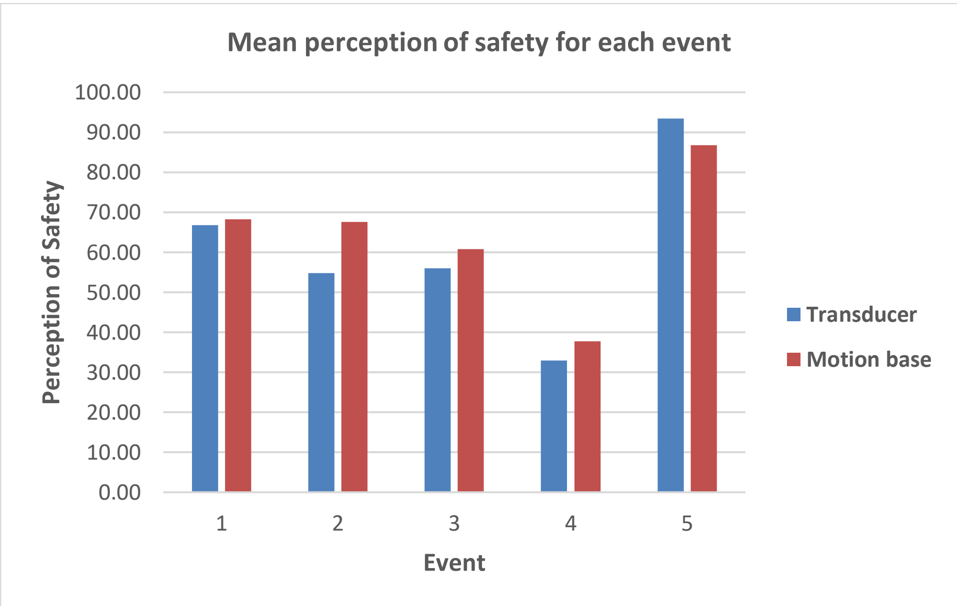


Figure 3.5 *Mean Perception of safety for each event*

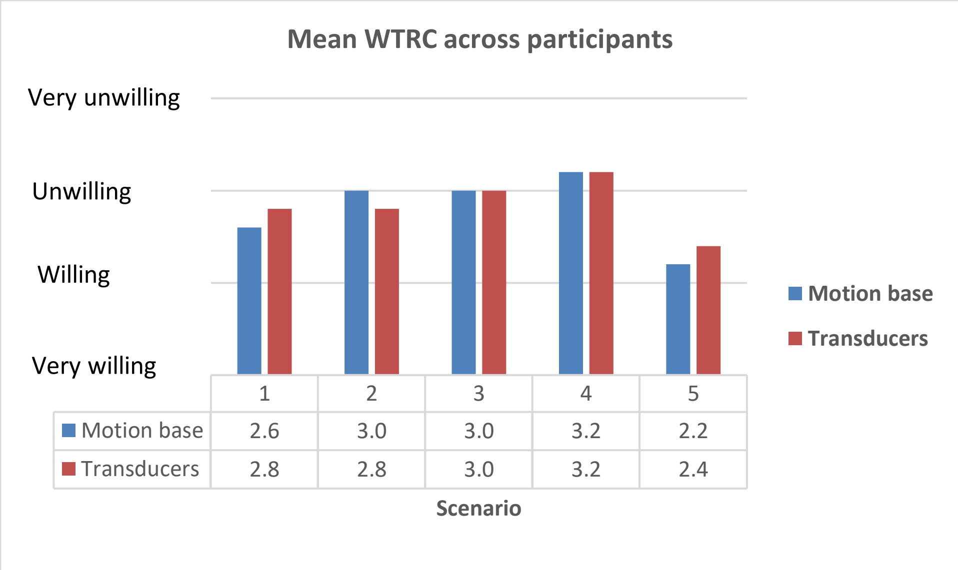


Figure 3.6 *Mean WTRC ratings across participants*

The purpose of the statistical analysis was to determine whether there were differences between ratings (WTRC and POS) given for the same scenarios in two experimental conditions. The GEE method is used to estimate the parameters of the generalised linear model with the possible unknown correlation between outcomes. It can be used for both ordinal and interval data. The unstructured working correlated matrix was selected for both WTRC and POS, being dependent variables. For modelling the dependent variables, the multinomial model and cumulative logit link function were selected for WTRC and the linear model and identity link function for POS. The independent variable was the experimental condition (real-time simulation with motion base or playback with tactile transducers). Participant identification code was the subject variable.

The results of GEE tests for WTRC and POS ratings are summarised in **Table 3.1**.

Table 3.1 *Results of GEE tests for WTRC and POS between two experimental conditions*

Event	Mean M/base	Mean Trans.	SD M/base	SD Trans.	POS.Wald $\chi^2(1)$	POS.p	WTRC.Wald $\chi^2(1)$	WTRC.p
1	66.80	68.20	22.60	19.14	0.246	0.620	1.405	0.236
2	54.80	67.60	21.00	21.45	0.744	0.388	1.810	0.179
3	56.00	60.80	21.00	22.88	0.155	0.694	1.169	0.280
4	33.00	37.80	14.85	15.91	0.275	0.600	0.000	1.000
5	93.40	86.80	8.76	19.31	0.339	0.560	1.169	0.280

Results of the last question, at the end of the experimental session where participants were asked to correctly identify the experimental condition, are illustrated in **Figure 3.7**.

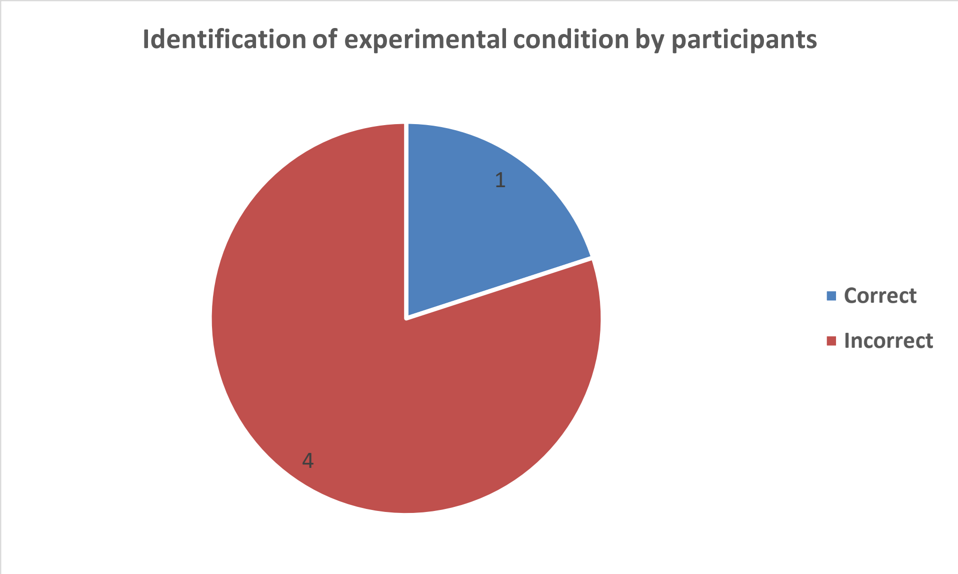


Figure 3.7 *Correct vs incorrect identification of experimental conditions*

Discussion and conclusions

The results were consistent for ratings of both WTRC and POS. There was no significant difference between ratings recorded in two experimental conditions for any of the scenarios. Moreover, four out of five participants incorrectly identified the experimental conditions. This means that they were not able to distinguish between the two conditions, falsely perceiving effects produced by tactile transducers as the output of a motion base. Although participants' focus was on what was happening on the road rather than observing vibrations and movements of the simulator car, this result is significant because it shows that under certain conditions such as driving on a relatively straight road and avoiding hard accelerations or braking, there is no significant difference in subjective perception between active motion base with three degrees of freedom and just vibrations of the motion base.

It is therefore concluded that tactile transducers produced vibrations that closely resemble actual motion base vibrations and can be used in the design of Study 3 (Willingness to engage or disengage automated control mode in Level 3 automated vehicle).

3.5 Development of real-time automated driving for Study 4

3.5.1 Introduction

As previously discussed, the EcaFaros v7.1 simulator software does not support simulation of automated driving mode apart from an extremely basic and unrealistic preview functionality that is not practical for research purposes. All previous studies have been designed without the need for switching driving modes during driving which was a potential limitation. However, the experimental design of Study 4 depended on the ability of the simulator to present realistic automated driving and allow switching between manual and automated control modes in real-time. Therefore, the development of an automated driving control algorithm and the implementation of the physical interface for switching between driving modes were required.

3.5.2 Automated driving control algorithms

EcaFaros application programming interface

The EcaFaros v7.1 simulator software API (application programming interface) allowed the creation of customised scenarios using an enriched version of JavaScript. The API offered several functions that allowed the replacement of "human" controls input with programmed logic. When engaged, these functions override inputs from peripheral devices and directly control the simulator vehicle model allowing precise control of each required vehicle command (steering wheel angle, throttle pedal position and brake pedal position in the case of automated driving). The frequency of updates to the vehicle model was 60 Hz. At the same time, a complimentary output function returned a real-time value of a selected control. The combination of these two functions for each of the vehicle controls (steering wheel, throttle and brakes) allowed the formation of a closed signal loop and therefore the implementation of an automated vehicle control logic.

Control parameters and error feedback

Two main processes were required to control the simulator vehicle. These were vehicle lateral movement and vehicle longitudinal movement. Under normal driving circumstances that exclude extreme situations such as tyre skidding or wheel locking, the lateral movement is controlled by a steering wheel angle input and lateral position error feedback. The error feedback provides information on the difference between the target position and the current position of the simulator vehicle in the lane. The longitudinal movement is controlled by a combination of throttle and brake pedals positions and the resultant velocity error feedback. The error feedback provided information on the difference between target velocity and the current velocity of the simulator car. Therefore, for both lateral and longitudinal control, a closed-loop control system was required. In such a system constant feedback is provided and desired output calculated continuously.

PID controller

The basis for the development of an automated vehicle control logic was a Proportional-Integral-Derivative (PID) control algorithm. PID controller is the most common control algorithm used in industrial applications (O'Dwyer, 2009) for control of process variables. It offers robust performance in a wide range of operating conditions while being functionally simple (National Instruments, 2019). The diagram of a basic PID controller is shown in **Figure 3.8**

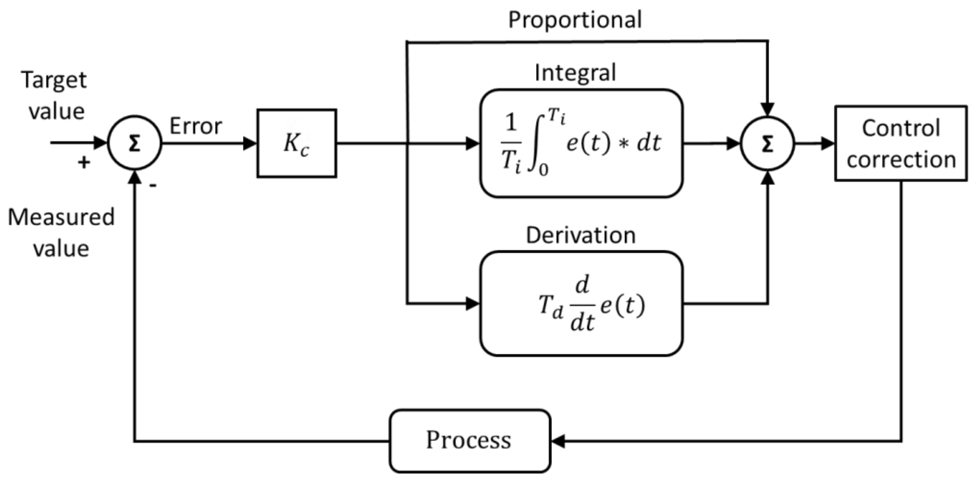


Figure 3.8 *A diagram of a basic PID controller*

The error is the difference between the target value and process output measured value. The target value is determined externally. For example, the target vehicle speed may be automatically determined by the speed limit of the road. Within the loop, the error signal is used to produce three components, proportional, integrated and derived. The sum of these provides a control signal for the process. The proportional component represents the current value of error. The integral component sums the error over time providing a cumulative error. The derivative component reacts to the rapid changes of error signal producing a damping effect. PID controller was proposed by Ioannou et al. (1993) for intelligent cruise control.

To get an ideal response for the control system optimal gains for P, I and D components needed to be set. A Ziegler-Nichols method (National Instruments, 2019) was used for the tuning process. In this method, I and D gains were set to zero and P was increased until the loop started to oscillate. Then K_p (proportional constant) and P_c (period of oscillations) were recorded and P, I and D gains adjusted according to values from the Ziegler-Nichols tuning table (**Table 3.2**).

Table 3.2 *Ziegler-Nichols tuning table*

Control	P	Ti	Td
P	$0.50K_p$	-	-
PI	$0.45K_p$	$P_c/1.2$	-
PID	$0.60K_p$	$0.50\ P_c$	$P_c/8$

Calculation of lateral position error due to road curvature

Various simulators differ in what information about road geometry is available to users. EcaFaros v7.1 simulator software uses a network of splines to control active objects in a scenario. The same network was used for the development of automated control mode. Splines are serial connected invisible vectors superimposed onto the physical terrain of the 3D graphics that form a virtual world. They are usually laid down in the geometrical centre of road lanes.

The roads in virtual 3D environments are constructed with a series of interconnected textured polygons. Roads contain both straight sections and bends. The road bends are formed with a finite number of connected, shorter straight sections. The size of each road segment depends on terrain elevation and the sharpness of the bend. As a result, splines also have different lengths and different angles between two connected splines. In practice, there are more graphics segments than spline segments which means that splines are not always perfectly aligned with graphics.

The primary error signal for maintaining lateral control was the distance from the current road spline, therefore, the centre of the lane. However, the automated steering based on the primary lateral position error was not able to achieve stable steering control apart from at very low speeds or at straight road sections due to sudden changes in error value and limited simulation frame rate.

When driving, human drivers observe the road ahead and make steering adjustments according to the road curvature and speed of travel. For a human driver, this is an automated process, a result of the skill gained through training and extensive practice. Therefore, such a process had to be replicated by the algorithm for the automated steering control of the simulator vehicle.

To accomplish a realistic steering control from the perspective of a human observer, the algorithm needed to anticipate road curvature ahead and initiate the steering action before entering a bend, similar to a human driver who is not observing position within the lane by just looking left and right but ahead at a distance ahead. This forward distance was proportional to the vehicle velocity. Also, the algorithm needed to address sharp changes in angle between consecutive splines.

This was achieved by calculating Lateral Position Error (LPE) as a function of simulator car velocity, distances from the start of each spline, lengths of each spline segments and angles between connecting splines. In the example below, the Lateral Position Error function that accounts for up to three splines ahead is presented. The three splines range was satisfactory for the road geometry and speed limits in planned simulator experimental drives.

Lateral Position Error (t) = f(n, v(t), d_{n+1}(t), l_{n+1}, α_{n+1}, d_{n+2}(t), l_{n+2}, α_{n+2}, d_{n+3}(t), l_{n+3}, α_{n+3}), where:

- n is the spline on which simulator vehicle is located;
- v(t) is real-time simulator car velocity;
- d_{n+1} (t), d_{n+2} (t) and d_{n+3} (t) real-time distances from simulator car to start of each spline;
- l_{n+1}, l_{n+2}, and l_{n+3} are lengths of each spline as referenced by spline n;
- α_{n+1}, α_{n+2} and α_{n+3} are angles between sequential splines as referenced by spline n.

An example of the geometry of splines in a bend is illustrated in **Figure 3.93.9**.

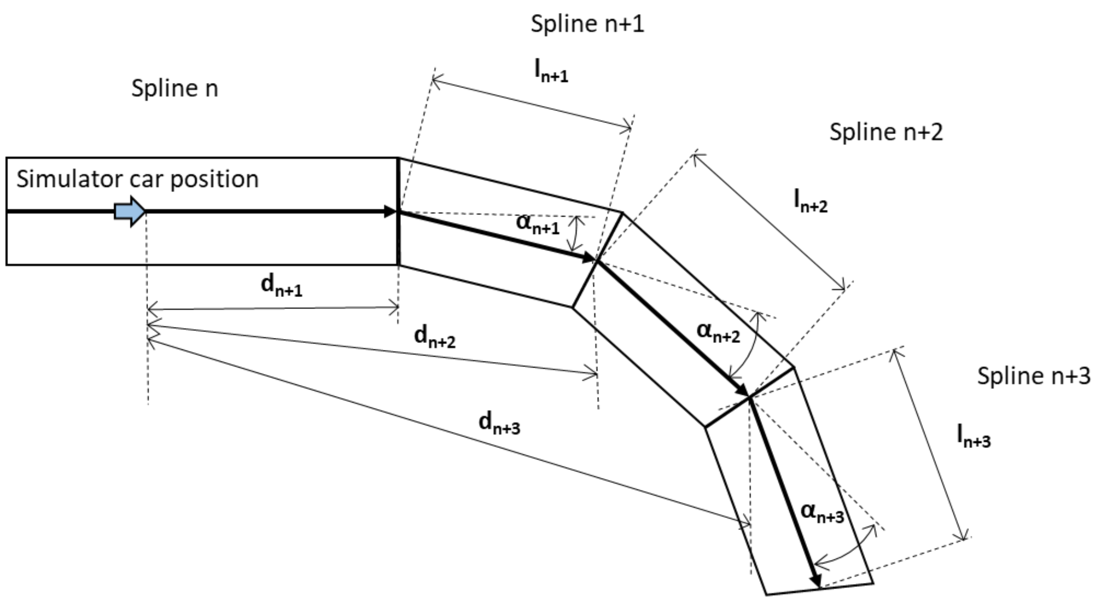


Figure 3.9 *Spline configuration in a road bend*

The issue of anticipatory feedback in automated steering has been acknowledged in the literature. Sharp, Casanova and Symonds (2000) proposed a comprehensive mathematical model for driver steering control joined to a vehicle dynamics model. Jamson et al. (2013) used this model in their study on automated driving to project look-ahead points in front of the vehicle before calculating error from the desired trajectory.

Incorrect mapping of splines

Parameters of every spline included in the database are stored in a formatted file. Each spline is described by its origin coordinates, length of the spline, preceding spline number, next spline number, speed limit, bifurcation spline and other fields. During testing of the automated driving many errors were discovered, such as the previous spline or next spline fields pointing to the wrong spline. All these errors had to be corrected manually for the automated driving algorithm to work properly. In addition to the above problem, the LPE (lateral position error) algorithm assumed that the numbering of splines was sequential and based on increments of 1. However, there were exceptions to this rule which had to be addressed individually within the algorithm.

Transitions between driving modes

In a Level 3 AV, two transitions are possible between automated and manual driving modes. The first type of transition was changing the driving mode from manual to automated. A set of restrictions was implemented for this transition. The automated driving mode could be safely engaged only if LPE is maintained within safe limits. Without these restrictions, if LPE values outside these limits were sustained over a certain time, the automated steering control algorithm could not establish a stable control loop on time and the car was likely to steer outside the road. For example, if a human driver in manual mode drove between road lanes (instead of within the lane), the simulator software would likely keep altering detected splines between splines on the left and splines on the right side of the simulator car, and therefore accumulating unrecoverable LPE value. Such loss of automated steering control was prevented by restricting the range of LPE inside the road lane within which the automated driving can be engaged. As a result, automated driving could not be engaged if the car was driven close to the edges of the road lane, in the wrong lane or outside roads. An additional clause was introduced to prevent switching on automated driving mode if a simulated car was travelling more than 5 km/h over the speed limit. The second type of transition was changing from an automated driving mode to a manual driving mode. There were no restrictions on when manual mode could be engaged.

3.5.3 Automated vehicle driving style

After stable automated driving was achieved on experimental roads, the focus was shifted to the question of how the automated vehicle should behave on the road. It is anticipated that vehicles with high-level automation would behave more robotic to reach all benefits of vehicle automation such as an increase in traffic flow efficiency or reduction in consumption of energy. For example, platoon driving requires the adoption of very short gaps between vehicles. However, an experimental session in the study was short and there was no time to teach and train participants to accept and trust machine-like driving. The additional issue would be the increased risk of motion sickness.

Several publications addressed the automated driving style. It was found that drivers when exposed to automated driving, preferred a more defensive driving style to their own (Basu et al., 2017; Yusof et al., 2016). (Horrey et al., 2015) suggested employment of learning algorithms to inform the automated system of the driver's abilities. Johns et al. (2016) found that a gentler automated driving style was generally more acceptable by drivers. Oliveira et al. (2018) found that human-like behaviour inspires confidence in automated driving due to familiarity. Therefore, it has been decided that for this research simulated automated driving should be defensive, consistent and predictable. Also, an attempt to achieve more anthropomorphic behaviour of automated driving was made such as replicating human choice of vehicle trajectory in road bends.

Adherence to speed limit

The automated driving mode speed was kept under the speed limit at all times. The speedometer displayed real speed. According to Australian Design Rules (ADR, 2018), displayed speed must be within a range of 0% to 10% above the actual speed of travel. As the simulator representation of absolute speed was not validated, the overrepresentation of speed was not considered relevant. Therefore, it was demonstrated to participants that the automated system would not exceed the speed limit in driving situations.

Acceleration and braking

Accelerations were kept smooth and controlled. Maximum acceleration and deceleration limits were set as well as maximum brake pressure. As a result, there was no hard braking during automated driving. Maximum accelerations of 0.1g and maximum decelerations of 0.2g were adopted from the specifications outlined by Ioannou et al. (1993).

Lateral position adjustments

The possible adjustments of lateral position in automated driving were evaluated for three specific situations. They were driving on straight roads, driving in bends and facing oncoming vehicles. For driving on straight sections of the road, a central position was determined to be natural and did not require any additional adjustments. Similarly, it has been decided that there was no need to alter the lateral position on straight roads when facing oncoming traffic.

However, driving in bends was made to appear more natural by iteratively adding and subtracting certain offset value to LPE for specific splines. As a result, automated driving lateral control appeared to follow a more efficient ("cutting corners") trajectory when entering and exiting bends similarly to a trajectory selected by a human driver instead of robotic adherence to the centre of the lane. This behaviour appeared more natural because experienced drivers would be inclined to preserve vehicle momentum and maintain the stability of the vehicle on the road. Also, the maximum angular speed of the steering wheel was limited to prevent any sudden lateral movements.

Motion base sensitivity

The motion base parameters such as pitch and roll sensitivity were adjusted at somewhat conservative levels to prevent reaching limits of movement range during the manual driving mode. This would feel unrealistic to the simulator driver. The vibration levels and balances were adjusted at a marginally higher level than what would be expected in a modern on-road vehicle to compensate for the reduced pitch and roll.

3.5.4 HMI for engaging and disengaging automated control mode

As study 4 was based on real-time automated driving, an interface for switching between automated and manual driving modes was required for the experimental drives. There were no current standards for this interface, however, researchers have been working on the design of HMI (human-machine interface) for automated driving.

Debernard, Önen, Chauvin, Pokam, and Langlois (2016) proposed methodologies for the design of such interfaces and attempted to answer what should be displayed, how and when. They suggested that the interface must allow the driver to establish accurate situation awareness during each driving mode as well as during transitions between driving modes. Carsten and Martens (2018) proposed a set of design principles for in-vehicle HMI. The HMI design in automated vehicles should provide a required understanding of the AV capabilities and status, produce correct calibration of trust, stimulate an appropriate level of attention and intervention, minimise automation surprises, offer comfort to the human user and be usable. Kasuga et al (2018) designed an HMI system to induce a smooth and safe transition to manual driving from Level 3 automated driving using voice guidance, alarm sound, HUD and interior lights. Ekman et al (2017) recommended that HMI designers and automated vehicle manufacturers take a more holistic perspective on the development of trust in the system.

The HMI interface required for interactive choice of vehicle control mode had to allow seamless transitions between manual and automated driving modes. The preferred location of the physical controls was on or close to the steering wheel, similarly to the cruise control button or stork in cars. However, there were certain limitations within the simulator software and hardware that restricted the number of feasible options. The simulator steering wheel, although producing force feedback when driven in manual mode, would simply return and remain at the neutral position when in automated driving mode. Therefore, having a fixed stoke or a button on a steering wheel could cause a certain temporal loss of steering control if manual control of the vehicle is resumed during the driving in a bend. The simplest solution was to separate automated driving control from the steering wheel and mount the pushbutton next to the steering wheel.

The chosen button was a large illuminated green momentary action switch **Figure 3.10**. The physical and electrical connection with the simulator software was provided via Universal Serial Bus (USB) interface. Jamson et al. (2013) used a somewhat similar interface (button) to engage and disengage automated driving in their experiment on behavioural changes in the highly-automated vehicle.

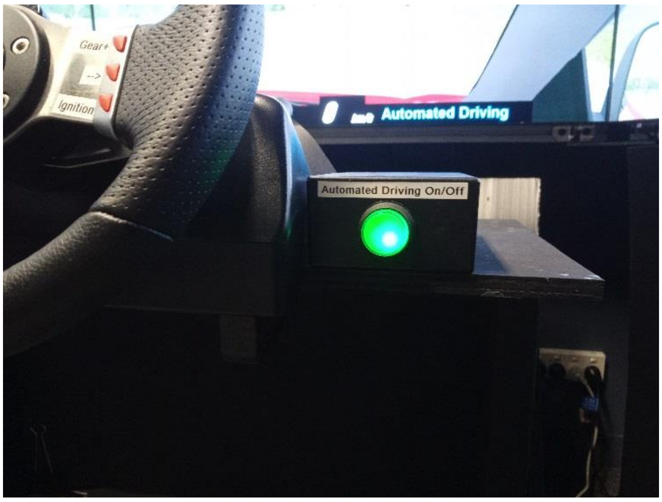


Figure 3.10 *Automated driving mode pushbutton*

As an illuminated pushbutton was used for the selection of vehicle control mode, several pushbutton illumination scenarios were evaluated. For example, the pushbutton could be illuminated when the automated control mode was active and dark when the manual control mode was active. However, permanent illumination was considered to be a useful feature to aid the location of the pushbutton with peripheral vision. Using peripheral vision for changing driving mode allows uninterrupted observation of a driving scene. As a result, the visual feedback on the active driving mode was provided on the screen as part of the virtual dashboard as a message. The message indicating currently active driving mode was permanently displayed during the simulation. The message indicating manual driving mode was “Manual Driving” and the messaged indicating automated driving mode was “Automated Driving”.

Since there were restrictions on when automated driving mode could be engaged, it was necessary to provide this feedback to the driver. This was achieved by altering the colour of the displayed message text, dependent on whether switching to automated driving mode was possible or not. If the message text was in blue (**Figure 3.11a**) switching was possible. If the message text was in amber (**Figure 3.11b**) switching was not possible.

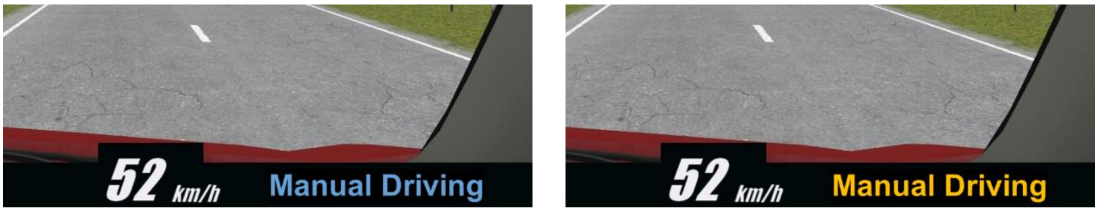


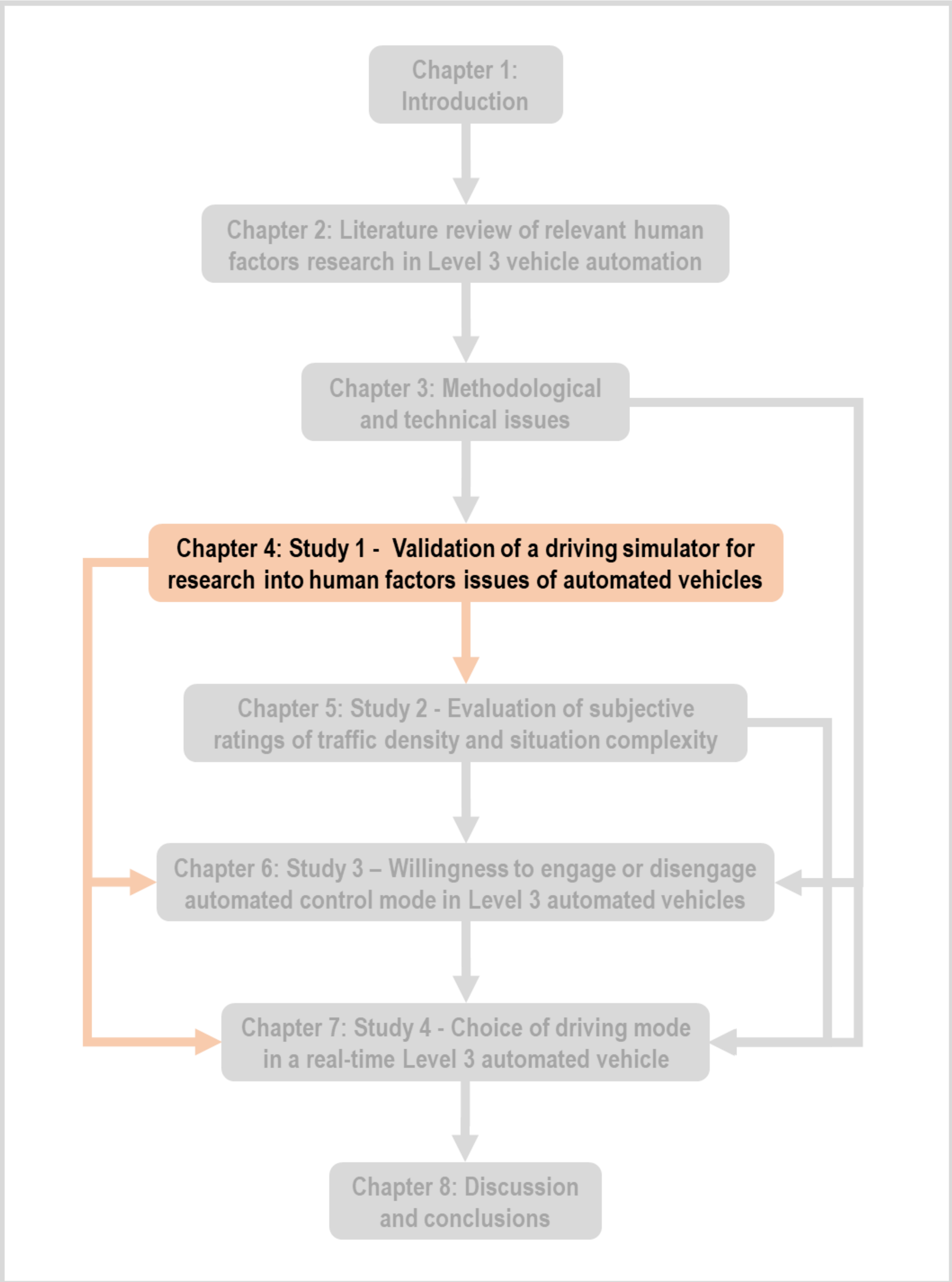
Figure 3.11 *Text colour indicating **a)** automation can be engaged and **b)** automation can not be engaged*

The text of the message displayed during automated driving was always in blue. This choice of colours was made to make two conditions visually easy distinguishable while avoiding possible unwanted associations that may come with other colour combinations such as green and red.

3.6 Conclusions

This chapter described the methodological and technological challenges encountered during the research program and discussed how they were overcome. This work facilitated the rest of the empirical research program. However, some of issues relevant to the research questions were identified during these activities such as HMI design and automated driving style. The next four chapters present the experimental research undertaken based on the resolved technical issues outlined in this chapter.

Chapter 4



Chapter 1: Introduction
Chapter 2: Literature review of relevant human factors research in Level 3 vehicle automation
Chapter 3: Methodological and technical issues
Chapter 4: Study 1 - Validation of a driving simulator for research into human factors issues of automated vehicles
Chapter 5: Study 2 - Evaluation of subjective ratings of traffic density and situation complexity
Chapter 6: Study 3 – Willingness to engage or disengage automated control mode in Level 3 automated vehicles
Chapter 7: Study 4 - Choice of driving mode in a real-time Level 3 automated vehicle
Chapter 8: Discussion and conclusions

Chapter 4 Study 1: Validation of a driving simulator for research into human factors issues of automated vehicles

4.1 Introduction

This chapter describes Study 1 in which the validation of a driving simulator for research into human factors issues of automated vehicles was undertaken.

4.1.1 Validation of driving simulator

Driving simulator cues

Simulators provide a safe, economical and controlled environment in which to conduct automation research. However, this is an artificial environment and some differences in experience when compared to driving a real car can not be avoided. It has been accepted that every driving simulator has its limitations which are directly related to the cues it can provide (Espié et al., 2005). These cues can be various aspects of visual, audio, vestibular, tactile and any other sensory experience. Even the most advanced or most expensive simulators today are not capable of perfectly replicating the real-world experience. These differences may influence the participants' behaviour. Hence, it is of critical importance that researchers understand the capabilities of an individual driving simulator. This understanding is the first step towards a successful simulator research study. Kaptein et al. (1996) stated that if the set of cues important to the subject of the investigation is available in the simulator, the simulator may be as valid as a field experiment. Therefore, to be used in automation research, a driving simulator needs to reproduce or instigate similar driver responses to those that would occur in the real road automated vehicle. This can be achieved only if relevant cues are presented to participants during simulator drive. In the case of automated driving, at the most basic level, the simulator needs to represent a realistic automated driving mode and functional HMI for selection of the driving mode, in addition to standard simulator specifications.

Simulator validity

As research simulators are commonly developed independently of each other and have distinct parameters (Godley et al., 2002), it is necessary to validate them on an individual basis. Espié et al. (2005) concluded that every simulator is *"a specific compromise dedicated to a certain number of usages"* (p. 6). Furthermore, every subsequent variation in simulator specifications could require a reassessment of the simulator.

The basic two aspects of simulator validity are physical and behavioural. The physical validity refers to how closely the simulator represents physical aspects of the real-world vehicle. It also evaluates the accuracy of the virtual 3D environment that is being represented, how realistic are vehicle models used and how realistic simulator scenarios are. Physical validity has also been referred to as simulator fidelity. Behavioural validity refers to the ability of the driving simulator to evoke the same responses as in a real-world environment. Furthermore, it is generally accepted that behavioural validity must be defined relative to a specific research question. The use of driving simulators should be preceded by the question of whether the simulator is sufficiently valid for the task or ability to be investigated (Diels et al., 2015). There are two main types of simulator behavioural validity, absolute validity and relative validity. The claim of absolute validity is founded on identical or near-identical numerical values obtained during experimental tasks in the simulator and the real on-road vehicle. For example, if identical speed is observed in both environments under the same experimental conditions, the simulator has been confirmed for absolute validity of speed perception. Relative validity is based on observation of the similar effect on driving performance in both driving simulator and on-road vehicle, such as similar magnitude and direction of change (Harms, 1992).

Validation for specific aspects

Historically, driving simulators are commonly validated for various specific aspects such as speed perception, vehicle dynamics, hazard perception and many more. Godley et al. (2002) evaluated a driving simulator for speed research establishing relative behavioural validity and relative validity for mean speed. McGehee et al. (2000) examined driver reaction and performance in an intersection crash scenario in the simulator and on a test track. The study produced statistically equivalent reaction times. Underwood et al. (2011) evaluated hazard perception in the simulator and on the road, observing similar patterns in behaviour in both settings. Östlund et al. (2006) conducted a simulator validation study for the investigation of driver distraction and found that the validity vas very high, especially on tactical and operational levels.

On the other hand, validation studies may identify a lack of validity for specific aspects. For example, Godley et al. (2002) reported a lack of absolute validity in their study as there were significant differences in observed speed between the on-road car and simulator. Similar discrepancies were reported in other simulator validation studies. (Fors et al., 2013) reported significant differences in mean speed and eye fixations. (Hallvig et al., 2013) observed lateral position difference between high fidelity simulator and on-road data. Zöller et al. (2019) found differences in braking behaviour between the real-world and the simulator equipped with a hexapod motion base. These findings suggest that validation is not always achievable even if simulator fidelity is considered to be high.

Validation for automated driving

As automated driving is a new field in the research of human factors in road safety, a study was needed to establish the behavioural validity of the available driving simulator. Behavioural validation involves a comparison of two systems during identical tasks and circumstances in terms of system performance and/or driver behaviour; measurement of physical and/or mental workload (physiological measurements); subjective criteria from drivers and evaluation of how well the simulator results align with real-world findings.

At the time of this study, there were very few studies concerning the validity of the driving simulator for research into automated vehicles. Eriksson et al. (2017) explored workload differences between a driving simulator and on-road drives in an automated vehicle. In this validation study, the authors argued that a driving simulator can be a valid tool for studying users’ interactions with automated driving systems. Pariota et al. (2017) observed the effects of connected automated vehicles on car-following behaviour in driving simulators and an instrumented vehicle. Although there were some differences in behaviour between environments, a consistency in-car spacing within each environment has been shown.

4.1.2 Aims and hypotheses

The aim of this study was to validate the use of a driving simulator for research in human factors of automated driving. More specifically, a validation study of relative behaviour was conducted which will establish a level of credibility and transferability of the simulator results into the real world. To the knowledge of the author, no other validation study had been conducted to answer this specific question in the context of Level 3 automated driving. Two main hypotheses were developed. The first hypothesis stated that subjective levels of WTE (willingness to engage automated driving) and its antipode WTRC (willingness to resume manual control of the vehicle) would be similar in comparable real-world and simulated environments. The second hypothesis stated that subjective POS (perception of safety) would be similar in comparable real-world and simulated environments. Therefore, subjective ratings of WTE/WTRC and POS were used to compare driver behaviour in two environments.

4.2 Method

The study was conducted at the Monash University Accident Research Centre. The data collection was conducted under semi-controlled experimental conditions. The on-road drive was conducted on real roads but followed a pre-defined route. The simulator drive was programmed to replicate the on-road test route in terms of length, road conditions and other controllable parameters. No safety-critical events were included in the experimental drives. As described in the previous chapter, the participants were seated in the passenger seat of both the on-road car and the simulator and did not have access to a steering wheel and control pedals. The researcher was in the driver's seat and controlled the vehicle. Participants were instructed to assume a situation in which they were behind the controls of a Level 3 automated vehicle that was operating in automated mode for the entire duration of the drive and that they could resume manual control of the vehicle at any time, but their task was just to answer the questionnaire.

4.2.1 Participants

A total of 20 participants took part in the study, 11 males and 9 females, ranging in age from 21 to 64 years, with a mean age of 36.8 years (SD = 11.2). The mean driving experience was 16.9 (SD = 11.51) years, ranging from 2 to 41 years. Participants were recruited from both Monash University (post-graduate and undergraduate students or staff) and from outside using personal contacts. Ethics approval was obtained from the Monash University Human Research Ethics Committee. Participants were required to have a full driver's licence and drive at least 5,000 km per year.

4.2.2 Equipment

The experimental on-road car was an instrumented Holden Commodore VE. It had a rear-wheel drive and an automatic transmission. In addition to the existing instrumentation that was not visible in the cabin, a wide-angle camera was used to record the front driving scene with audio. The MUARC Automation Driving Simulator (**Figure 4.1**) was equipped with an additional passenger seat, mounted on its motion base that moved in unison with the driver seat motion base. The simulator vehicle represented a car with an automatic transmission. The same wide-angle camera from the instrumented car was used to record the simulator front scene with audio.

Figure 4.1 *Automation driving simulator setup*

4.2.3 Experimental questions

A tablet (iPad) was used to collect participant ratings of WTRC (willingness to resume control of the vehicle) at various points in the drives, as well as ratings of POS (perception of safety) during the simulator and on-road drives. There were between 20 and 25 questions for each drive and a final overall question completed after the end of the drive. Each question consisted of two parts B. Part A (**Figure 4.2a**) asked participants to rate their WTRC in the current situation. Participants were required to make a choice using a four-point Linkert scale. Four categories were available: very willing, willing, unwilling and very unwilling. The four-point scale was chosen to differentiate this scale from the 100-point scale used to rate POS in Part B of each question. A neutral option was omitted to force participants to form an opinion. Support for using a scale with a small number of response categories is provided by Contractor & Fox (2011) who found that 5 and 6 point scales may be more sensitive than scales with 7, 9 or 10 categories. Part B (**Figure 4.2b**) asked participants to rate POS in that situation using a linear scale from 1 to 100 (1 for very unsafe and 100 very safe).

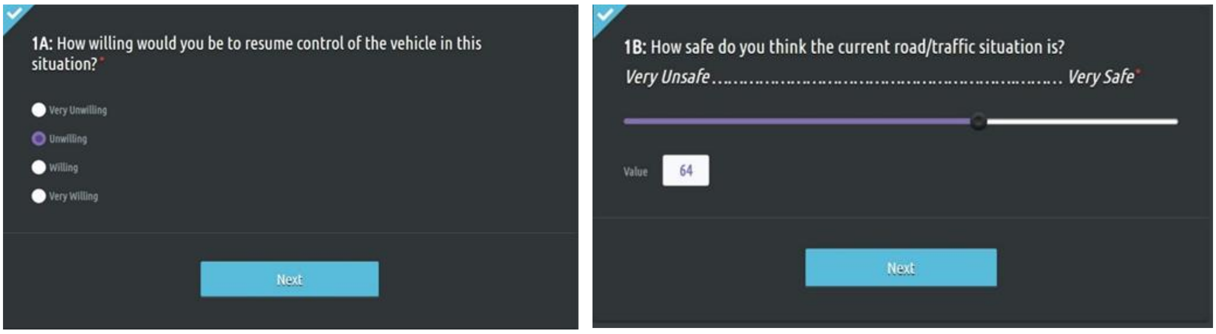


***Figure 4.2** Example of **a)** Part A (WTRC) and **b)** Part B (POS) question at a decision point*

4.2.4 Selection and matching of the simulator and on-road routes

The on-road and simulator routes were selected to resemble each other as much as possible, taking into account available equipment, time constraints and resources. Overall factors that had to be considered were:

- The total duration of each drive needed to be kept under 30 minutes;
- Total distance travelled during drives needed to be limited to under 20 km;
- The proportion of freeway driving vs urban/residential driving had to be similar;
- The density question points should be similar.

Specific environmental factors for the on-road drives were:

- Time of the day was between 11:00 and 15:00. This prevented sun glare situations and provided optimum visibility on the road;
- Peak traffic conditions had to be avoided; and
- Adverse weather conditions had to be avoided (dry roads only).

The following matching criteria between on-road and simulator scenes were used:

- Road lane width;
- Speed limits;
- Number of roundabouts;
- Number of turns;
- Number of freeway entries and exits;
- Number of road bends;
- Traffic density and composition;
- A number of signalised intersections.

The simulator drives were scripted and therefore the same events were presented to each participant. However, during the on-road drives, it was not possible to present every event to all participants. Only events that occurred in both the simulator and on-road drive for each participant were included in the analysis. The on-road route is illustrated in **Figure 4.3** (*Notting Hill, VIC, Australia*, 2019). The freeway section is marked with green M1 indicating the Monash Freeway. The rest of the drive represented an urban environment that consists of residential and arterial roads.

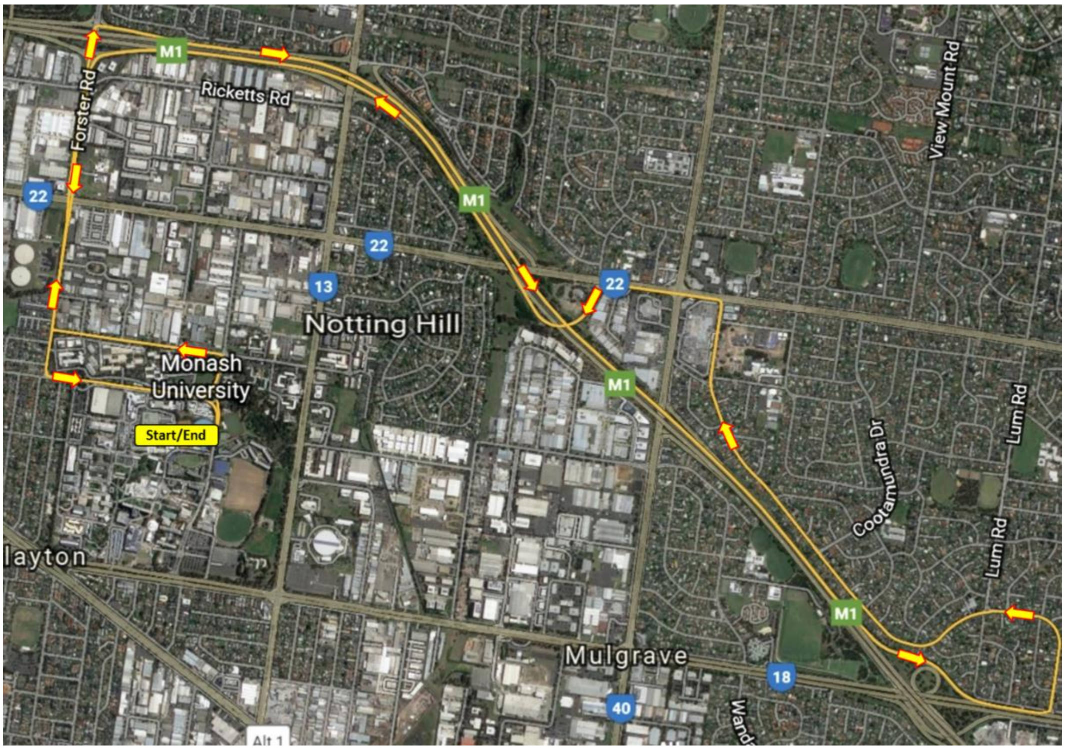


Figure 4.3 *On-road experimental drive route*

The simulator route is illustrated in **Figure 4.4**. The driven path is superimposed on the map of the virtual environment.

Figure 4.4 *Simulator experimental drive route*

4.2.5 Experimental procedure

Upon arrival, participants completed an informed consent form and read the experimental instructions. They were then given a brief introduction to automated vehicles and presented with the following definition of willingness: “Ready or eager to do something; Disposed or inclined; Prepared, or Acting or ready to act gladly.” This was followed by a demographics questionnaire that also included questions about driving habits, confidence and attitudes toward technologies. Before the start of experimental drives, participants had a short practice in responding to verbal instructions and entering their answers using a tablet. During this practice, five question points were presented with a pre-recorded video of on-road driving.

The order of the simulator and on-road drives was counterbalanced across participants. Half of the participants completed the simulator drive first and the other half completed the on-road drive first. Before and after each simulator drive, participants were administered a Well-being questionnaire to minimise the possibility of a simulator-induced discomfort. During both drives, participants were given a tablet which was used to record their ratings of WTRC and POS. During the drives, participants were instructed to observe the road and wait for the researcher’s verbal instruction: “Ready ... Now!”. The instructions were given with enough lead time for the participant to evaluate the situation ahead. After hearing this cue, participants were instructed to stop observing the road and quickly complete Part A and Part B of the question. After completing the question, participants would continue observing the road until the next question point. After the end of each drive, participants were asked to rate their overall WTE (willingness to engage automated driving) and overall POS based on the entire drive experience. The experimental procedure is illustrated in **Figure 4.5**. The duration of the experiment was between 90 and 105 minutes. At the end of the experimental session, participants were offered $30 for their participation.

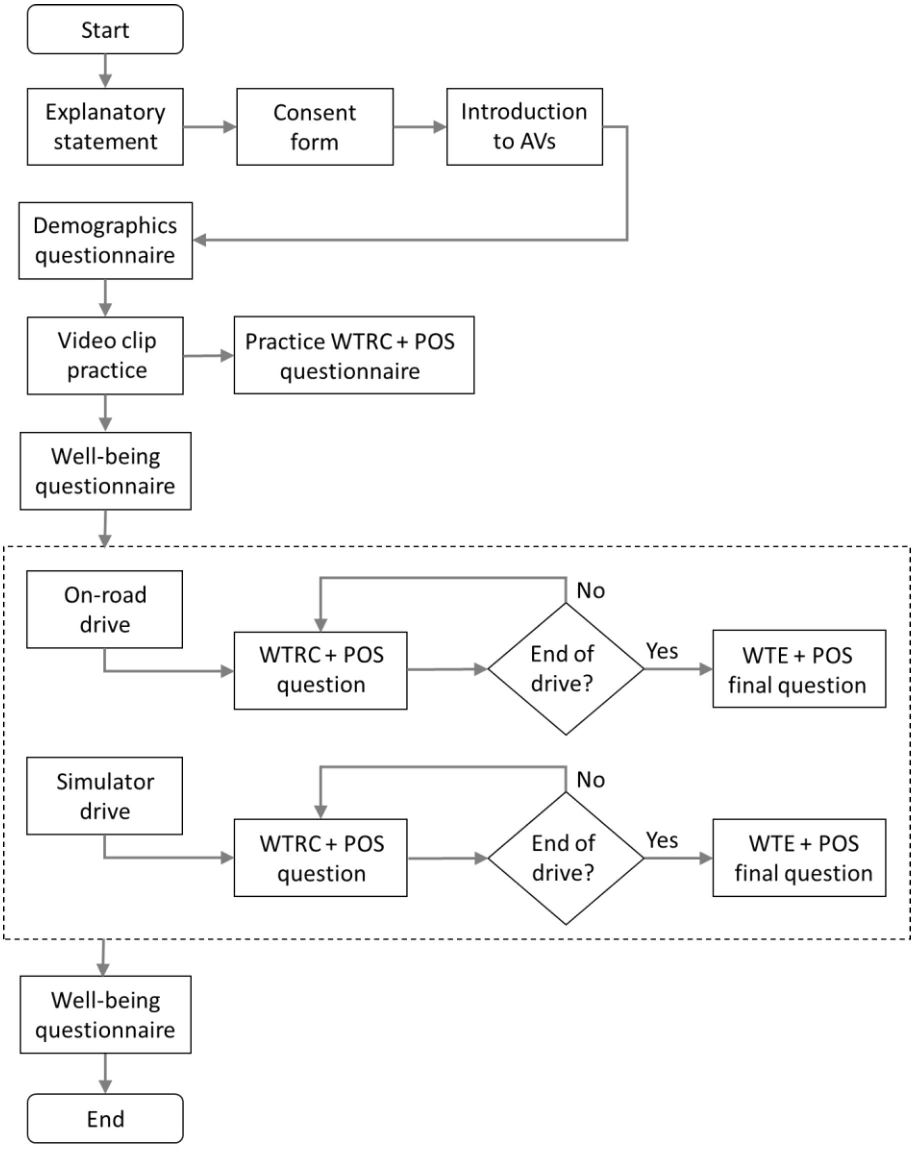


Figure 4.5 *Flowchart of Study 1 procedures*

4.2.6 Data collection and coding video recordings of events

During the drives, the following data were collected:

- Video recordings of the road scene;
- Subjective ratings of WTRC/WTE and POS;
- GPS and vehicle data (on-road drives only);
- Simulator data (simulator drives only);
- Pre-drive and post-drive well-being questionnaires (simulator drives only).

Using recorded video data, each decision point from every drive was coded for several parameters. They were: time, event type, road environment, speed limit, road division, number of lanes, road shape, traffic density, situation complexity and participant comments.

The video timestamp was used to identify question points in video files and to match them with other recorded data. Event type and driving environment were used as independent variables in data analysis. Other parameters were used to add more precision to the description of each question point. Some of these parameters were used to group data for statistical analysis.TD (traffic density) and SC (situation complexity) were selected to identify conditions for the statistical analysis. TD and SC of each event were rated as low, medium and high according to the criteria below. The criteria for determining TD levels were partially based on the SHRP2 (Strategic Highway Research Program 2) researcher dictionary for video reduction data levels of traffic density (VTTI, 2015). These criteria are presented in **Table 4.1**.

Table 4.1 *TD (traffic density) levels criteria*

TD Level	TD Criteria
Low	Free flow, no lead traffic (0-1 cars ahead within 5s TH (time headway), minimum TH > 3s)
	Freedom to select speed, change lanes and make turns (no vehicles in left or right lanes relative to the participant within 20m radius)
Medium	Free flow with some restriction (1-3 cars ahead within 5sTH, 2-3s TH)
	Freedom to select speed, change lanes and make turns (vehicle or vehicles in left or right lanes relative to the participant, within 10 – 20m radius)
High	Forced traffic flow conditions (3+ cars ahead within 5 seconds TH, minimum TH < 2s)
	Limited freedom to select speed, change lanes and make turns (vehicle or vehicles in left or right lanes relative to the participant, within 10m radius)

The SC levels employed, partially based on Cabrall and Winter, (2017), de Craen et al. (2008), and Fastenmeier and Gstalter, (2007) are presented in **Table 4.2**.

Table 4.2 *SC (situation complexity) levels criteria*

SC Level	SC Criteria
Low	No significant cognitive processing is required (clear road, smooth and predictable traffic)
Medium	Some cognitive processing required (traffic ahead, approaching intersections or turns)
High	Medium to intensive cognitive processing required (dealing with vulnerable or unpredictable road users, complex intersections, aggressive drivers, reduced visibility)
	Critical decision making (merging, overtaking, potential emergency braking)

Based on these criteria, a single rater assigned levels of TD (traffic density) and SC (situation complexity) to every individual event encountered in experimental drives. Comparisons of all score distributions across three levels between on-road and simulator drives are illustrated in **Figure 4.6a)** for TD and **Figure 4.6b)** for SC, confirming relatively similar patterns in both experimental environments.

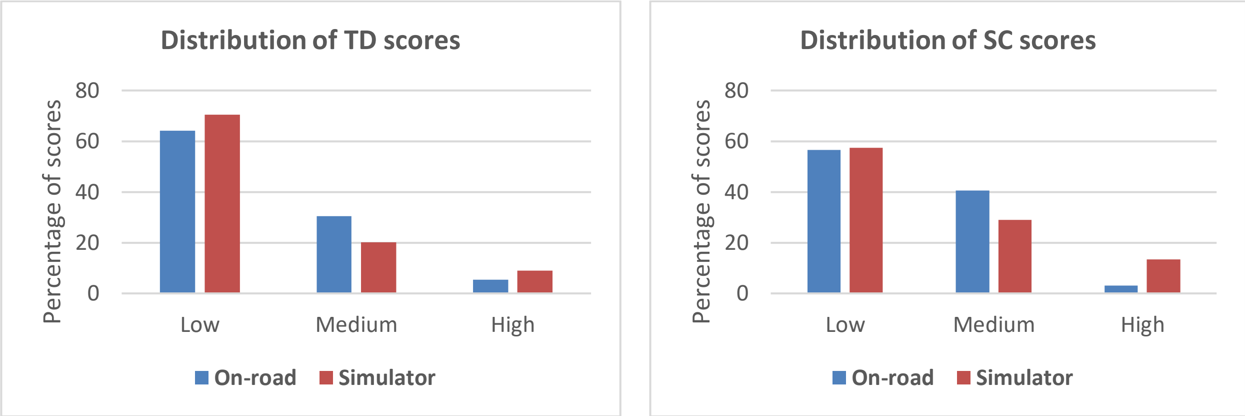


Figure 4.6 *Distributions of **a)** TD scores and **b)** SC scores*

4.3 Results

The purpose of the statistical analysis was to determine whether there were differences between ratings of WTRC/WTE and POS for similar decision points and conditions across the simulated and on-road driving environments. GEE (Generalised Estimating Equations), (Zeger & Liang, 1986), with the identity link and an unstructured correlation matrix were used to test the main effects of the independent variable on self-reported WTRC/WTE and POS across different events and event categories. GEE can be used for both ordinal (WTRC/WTE) and interval data (POS) and require a single entry of the dependent variable for each condition of the independent variable and each subject. In cases where multiple records existed for a category such as conditions, the median value was used for ordinal variables (because the data were non-normally distributed) and the mean for linear variables.

4.3.1 Willingness to resume control and willingness to engage automated driving mode

For modelling the WTRC and WTE, the multinomial model and cumulative logit link function were selected. The independent variable was an experimental environment (simulator or on-road). The dependent variable was self-reported WTRC for all drive events and conditions and WTE for the final question. Participant identification code was the subject variable.

Tests of main effects for all events and conditions are summarized in **Table 4.3**. The table contains a list of all tests conducted on events and driving conditions. Results are presented as model effects for WTRC for every event and condition and WTE for the final question. Events and conditions that produced statistically different results ($p < .05$) are highlighted. The results for the final questionnaire item, which represents overall WTE ratings for the whole drive revealed that there were no significant differences across the on-road and simulator environments for WTE ($\chi^2(1) = .937$, $p = .324$). There were no significant differences across environments for WTRC ratings for the majority of events. They were free driving on the freeway, free driving on urban roads, vehicle following, left bend, roundabout, give way/stop sign, congestion, stopped bus, and pedestrian events. Events that produced significant statistical differences in WTRC ratings were merging on the freeway and uphill road.

Statistical test of WTRC for a large majority of conditions (levels of traffic density and situation complexity) indicated that there were no significant statistical differences between the on-road and simulator environments. The only exception was medium traffic density on the freeway.

***Table 4.3** Summary of Tests of Model Effects for WTRC/WTE*

Test	Wald Chi-Square	df	Sig.
Final Question	.973	1	.324
Free Driving (Freeway)	1.800	1	.180
Free Driving (Urban)	2.145	1	.143
Vehicle Following	3.543	1	.060
Left Bend (Freeway)	1.564	1	.211
Roundabout	.110	1	.740
Give Way/ Stop Sign	.197	1	.657
Merging (Freeway)	9.654	1	.002
Changing Lanes	.484	1	.486
Congestion*	2.898	1	.089
Stopped Bus*	1.708	1	.191
Pedestrians*	1.071	1	.301
Uphill road*	5.976	1	.015
Low TD (Urban)	.004	1	.951
Medium TD (Urban)	.000	1	1.000**
Low TD (Freeway)	3.406	1	.065
Medium TD (Freeway)	5.464	1	.019
Low SC (Urban)	1.710	1	.191
Medium SC (Urban)	.147	1	.701
Low SC (Freeway)	1.739	1	.187
Medium SC (Freeway)	1.529	1	.216
High SC (Freeway)*	.002	1	.968

*Events that did not have a full dataset (< 50%)

**Repeated GEE model analysis with only two categories of WTRC (willing and unwilling)

The above results are further illustrated with graphs and tables below, showing comparisons of mean WTRC (willingness to resume control) between on-road and simulator conditions for events (**Figure 4.7**) and conditions (**Figure 4.8**). For this exercise, each WTRC category was assigned a value as follows: 1 for very unwilling, 2 for unwilling, 3 for willing and 4 for very willing.

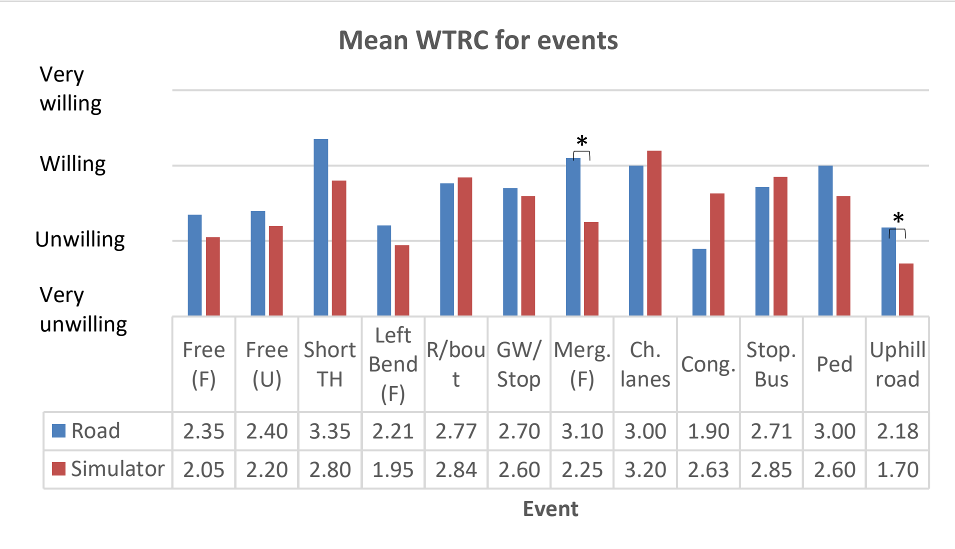


***Figure 4.7** Comparison of mean WTE between on-road and simulator for events (* p<0.05)*

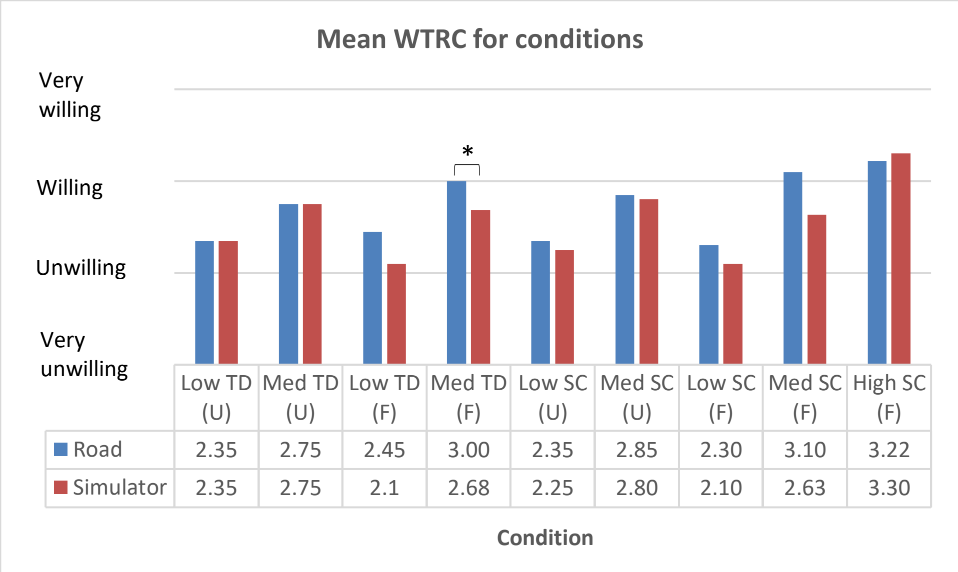


Figure 4.8 *Comparison of mean WTE between on-road and simulator for conditions (* p<0.05)*

4.3.2 Perception of safety

For modelling POS (perception of safety) as the dependent variable, the linear model and identity link function were selected. The independent variable was the experimental environment (simulator and on-road). Participant identification code was the subject variable.

Tests of POS model effects for all events and conditions are summarized in **Table 4.4**. The table contains a list of all tests conducted on events and driving conditions. Results are presented as model effects for POS.

The results for the final questionnaire item, which represents a general POS rating for the whole drive revealed that there were no significant differences across the on-road and simulator environments for overall POS ($\chi^2(1) = 1.010$, $p = .315$). The mean POS for the simulator drives (73.30) was marginally higher than POS for the on-road drives (70.75) with respective standard deviations of 3.89 and 3.59.

Among events, there were no significant differences across environments for POS ratings for free driving on the freeway, vehicle following, left bend, roundabout, give way/stop sign, congestion, stopped bus, and pedestrian events. The comparison of mean POS between the simulator and on-road events is illustrated in **Figure 4.9**. Events that produced significant statistical differences in POS ratings were free driving on urban roads, merging on the freeway, changing lanes and uphill road. The mean POS for free driving on urban roads was 69.08 (SD =3.29) and 75.75 (SD = 2.98) for on-road and simulator respectively. Merging on freeway mean POS was 56.63 (SD = 4.20) for on-road and 74.15 (SD = 3.12) for simulator. Changing lanes mean POS were 75.93 (SD = 5.17) for on-road and 51.65 (SD = 4.54) for simulator. Uphill road mean POS was 72.43 (SD = 4.17) for on-road and 86.55 (2.38) for simulator.

Table 4.4 *Summary of Tests of Model Effects for POS*

Test	Wald Chi-Square	df	Sig.
Final Question	1.010	1	.315
Free Driving (Freeway)	3.758	1	.053
Free Driving (Urban)	14.715	1	.000
Vehicle Following	.420	1	.517
Left Bend (Freeway)	.057	1	.811
Roundabout	.911	1	.340
Give Way/ Stop Sign	.473	1	.492
Merging (Freeway)	15.843	1	.000
Changing Lanes	4.561	1	.033
Congestion*	2.325	1	.127
Stopped Bus*	2.563	1	.109
Pedestrians*	1.037	1	.309
Uphill road*	12.674	1	.000
Low TD (Urban)	.801	1	.371
Medium TD (Urban)	.059	1	.808
Low TD (Freeway)	.067	1	.796
Medium TD (Freeway)	.055	1	.815
Low SC (Urban)	1.273	1	.259
Medium SC (Urban)	1.057	1	.304
Low SC (Freeway)	2.59	1	.125
Medium SC (Freeway)	4.004	1	.045
High SC (Freeway)*	1.979	1	.160

*Events that did not have a full dataset (< 50%)

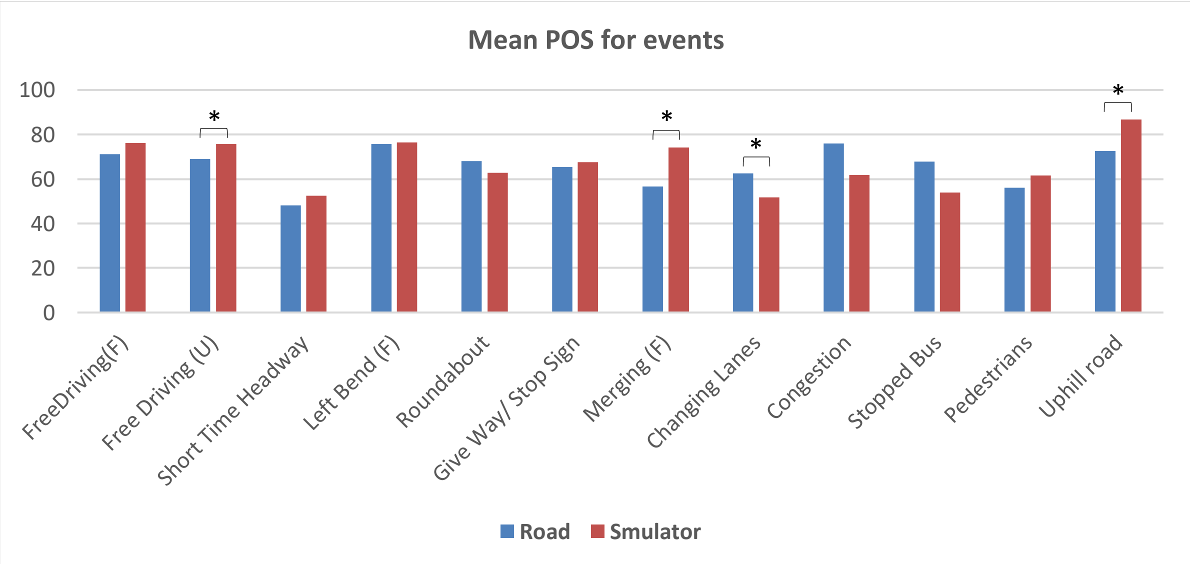


Figure 4.9 *Comparison of mean POS for events (* p<0.05)*

Statistical test for POS on conditions (levels of traffic density and situation complexity) indicated that there were no significant statistical differences between on-road and simulator environments. The only exception was medium situation complexity on the freeway. Mean POS observed during this condition was 56.70 (SD =

4.47) for on-road and 63.38 (3.80) for simulator. The comparison of means for each condition is illustrated in **Figure 4.10**.

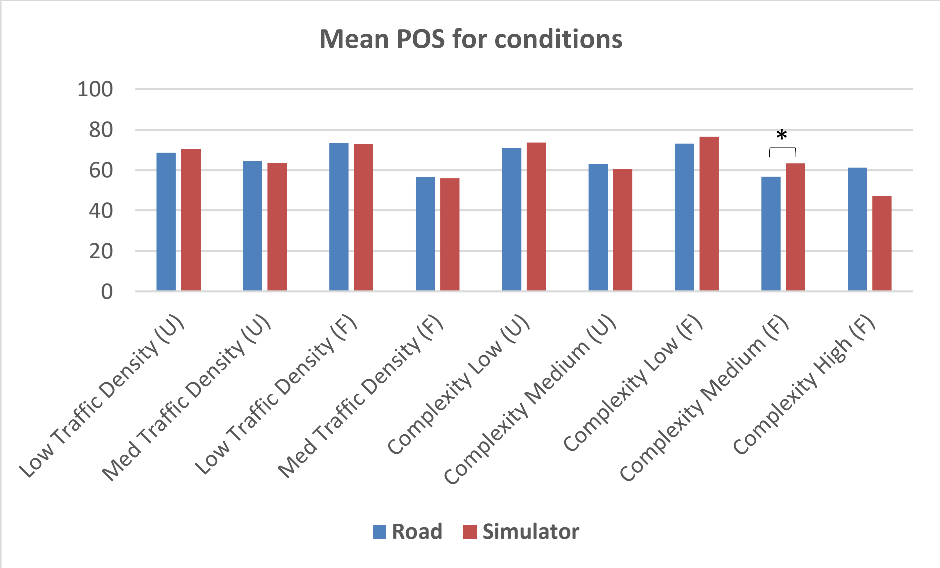


***Figure 4.10** Comparison of mean POS for conditions (* p<0.05)*

4.4 Discussion and conclusions

4.4.1 General findings and conclusion

The results revealed that for the large majority of events and conditions, there were no statistically significant differences in ratings of WTRC, WTE and POS across the two driving environments. The demonstrated similarity between subjective WTRC and WTE under relatively comparable conditions provided acceptable evidence that the evaluated driving simulator is a suitable environment for conducting this research.

Therefore, these events and conditions were well represented in the simulator when compared to the on-road environment in the context of the research question. This is supported by Kaptein et al (1996) who stated that, if the results between the simulator and the field experiment are similar, the simulator is shown to be valid for investigating the studied driving task.

From the perspective of further research (planned simulator studies), it was more interesting to understand the differences in experimental conditions that may have contributed to the significant statistical differences. These findings would be applied to future simulation studies in the research program to avoid possible confounding errors.

4.4.2 Events and conditions that produced statistically significant differences

Two events produced statistically significant differences in ratings for both POS and WTE between the experimental conditions. They were merging onto the freeway and free driving on an urban road. In addition to these events, the condition of medium TD on the freeway produced a significant difference in WTRC ratings but no difference in POS ratings. Free driving on an urban road, changing lanes event and medium situation complexity on freeway produced significantly different ratings for POS but not for WTRC. Each of these events and conditions is discussed in more detail in this section.

Merging onto freeway

In comparison to the on-road event, simulator event was perceived as much safer by 17.52 rating points. This was a very large difference as reflected in a statistically significant main effect of experimental environment for both WTRC and POS. When comparing video recordings of this event from these two environments, it was easy to observe that the freeway merging event in the simulator was distinctively simpler. There were fewer cars present in the simulator scene resulting in a less complex task, therefore demanding less driver workload. Merging onto a freeway could be classified as an event that demands intense cognitive processing. This event involves the execution of several simultaneous actions (changing lanes, adjusting speed, finding gaps, and continuously scanning the scene) while travelling at a relatively high speed, often in medium or high traffic density. It was speculated that such a high-complexity event exposed a difference in perceived real-life stakes that can not be replicated in the simulator.

Although the merging event in the simulator could be made more demanding by increasing the complexity (additional traffic and less unpredictable behaviour of other vehicles), further research is needed to answer how exactly perceived risk and driving task demands correlate under the simulator and on-road conditions. For example, in their simulator study on effects of cognitive and visual loads in real and simulated driving, (Östlund et al., 2006) found that less realistic risk in the simulator resulted in less level of stress.

Uphill driving

Uphill driving on the urban road was intended as a relatively simple and undemanding event with the expectation of low POS. The complexity of the event is derived from having a somewhat restricted view ahead (beyond the hillcrest). However, statistical tests indicated a significant difference in the POS ratings between environments (14.12 rating points), with the uphill section of the uphill driving event being rated as less safe in the on-road environment. Due to limitations in the range of available roads, not all experimental conditions could be accurately matched between two driving environments. In the simulator drive, this event occurred on the four-lane divided road, while in the on-road drive the same event occurred on a two-way undivided road Comparison of video recordings for this event from both environments exposed the difference in total road width and difference in secondary visual features such as parked vehicles, trees on nature strips, pedestrians on a footpath. To participants, the on-road event appeared as less safe (mean POS = 72.43) than the simulator event (mean POS = 86.55). These observations are supported by Fildes, Leering, and Corrigan (1989) who investigated drivers' judgement of safety and found that road width and the number of lanes had the strongest influence on judgements of safety and travel speed, while the roadside environment also had an effect, to a lesser degree. In their study, the divided road was perceived as significantly safer compared to the two-way undivided road. Therefore, it is not surprising that ratings of WTRC were statistically different for this event as well.

Medium traffic density (Freeway)

There was a significant difference in WTRC for the medium traffic density (freeway) condition but no significant difference in POS. This means that participants perceived this condition equally safe in each environment. However, their willingness to resume control of the vehicle was significantly different. The exponential parameter model estimate indicates that drivers were 2.5 times more likely to increase the level of their subjective willingness to resume control of the vehicle in on-road conditions. It has also been speculated that the medium level of traffic density may be perceived differently between participants and contribute to the difference in WTRC scores.

Free driving (Urban)

There was a significant difference in POS ratings for free driving on urban roads, but no significant difference in WTRC ratings. Free driving in the simulator (mean POS = 75.75) was rated as safer than on-road condition (mean POS = 69.08). The speed may be a confounding factor. While urban driving speed limit in the simulator was always 50 km/h, on-road urban speed limits were ranging from 50 km/h to 70 km/h, therefore, contributing to the reduced perception of safety. Additionally, the on-road drive generally contained more secondary visual features (such as parked cars, pedestrians, vegetation, etc.) providing more potential safety concerns for participants. Also, roads in the simulator environment more often contained sections with divided lanes thus increasing the perception of safety.

Changing lanes

There was a significant difference in POS ratings for changing lanes event but no significant difference in WTRC ratings. This event was perceived as safer in on-road condition by 9.83 rating points. This difference may be explained by a limited field of view of the scene in the simulator that adversely affects situational awareness. Simulator participants were restricted to up to 145° of HFOV (horizontal field of view) while there were no such restrictions in the on-road drive. For example, a blind spot check could not be performed in the simulator.

Medium situation complexity (Freeway)

There was a significant difference in POS ratings for medium situation complexity on the freeway but no significant difference in WTRC ratings. However, the difference between WTRC ratings was not statistically significant. The mean POS for the on-road condition was 56.70 while mean POS in the simulator was 63.38. The simulated freeway condition was perceived as significantly safer (by 6.68 rating points) than on-road condition. It has also been speculated that the medium level of situation complexity may be perceived differently between participants and affect the POS ratings.

4.4.3 Study limitations

Limited field of view in the simulator

The most glaring limitation of the driving simulator was limited FOV (field of view) as large FOV is recommended for accurate perception of vehicle speed and distances (Kemeny & Panerai, 2003). It can be speculated that limited FOV in the simulator contributed to differences in ratings of WTE and POS between the two environments. Mourant et al. (2007) investigated the effect of optic flow by manipulating the geometric field of view in the driving simulator. This study was conducted with a relatively narrow display (45°). They found that the speed production was overestimated and that the error was larger with lower GFOV (geometric field of view). Diels and Parkes, (2010) explored the effects of geometric field of view/display field of view on the perception of speed in the driving simulator with a wide horizontal field of view (210°). They too found that visual speed was consistently underestimated and attempted to compensate the error by manipulating GFOV/FOV ratio. They concluded that the optimum ratio for their simulator was 1.22:1. That means that certain events may have appeared less safe or safer dependent on the nature of the event and the available HFOV (horizontal field of view) in the simulator. For example, events may be perceived as safer due to underestimated speed, or less safe due to the inability to visually scan the scene beyond available FOV. As a result, special attention must be paid to the design of simulator scenario events to ensure that events do not require the participant to scan across wider FOV than what is available in the simulator, such as a blind-spot check. Also, if the effects of speed are investigated, the difference between speed conditions must be very noticeable.

Accurate representation of events

It is important to accurately represent an event in the simulator, however, differences between the real and simulated environments are likely to emerge regardless of the cost of the driving simulator. For example, Diels et al. (2015) conducted a behavioural validation of the driving simulator and found that mental workload tends to be moderately higher in the driving simulator. Harms et al. (1996) concluded in their summary that increasing the face validity of the VTI driving simulator does not necessarily enhance the overall behavioural validity of the simulator. For example, the simulator will always be safer environment compared to real-roads (Espié et al., 2005). For this study, however, the best effort has been made to accurately represent on-road events in the simulator.

Frequency of question points

For future experimental design it is important to find an optimal balance between the number of decision points and the duration of the drive. Too many points are likely to disrupt the immersion in the simulation while using too few points would be inefficient. Some of the variations in subjective ratings could be the result of the short time between consecutive question points. These short times between question points may have contributed to the increase of perceived mental workload and degradation of hazard perception (Borowsky et al., 2016) therefore affecting ratings of both WTRC and POS. Having a longer time between question points allows a participant to get immersed in the scene and recover to a normal level of mental workload.

Participant seating position

Given that an automated vehicle was not available for this study and Level 3 automated vehicles are not legally allowed to travel on Australian roads, a protocol was adopted whereby participants sat in the front passenger seat of the real and simulated vehicles which were driven by an experimenter. Participants were asked to imagine that they were in the driver's seat of an automated vehicle and answer the questions from this perspective. This method may, of course, lead to differences in participants' perception of safety and willingness to resume control of the vehicle. However, it has been estimated that these limitations had only a small impact because the main task was to enter ratings in the questionnaire (WTRC and POS) and not to drive or respond to take over requests. This limitation was further minimised by keeping both conditions as similar as possible in terms of the experimental protocol.

4.4.4 Conclusions

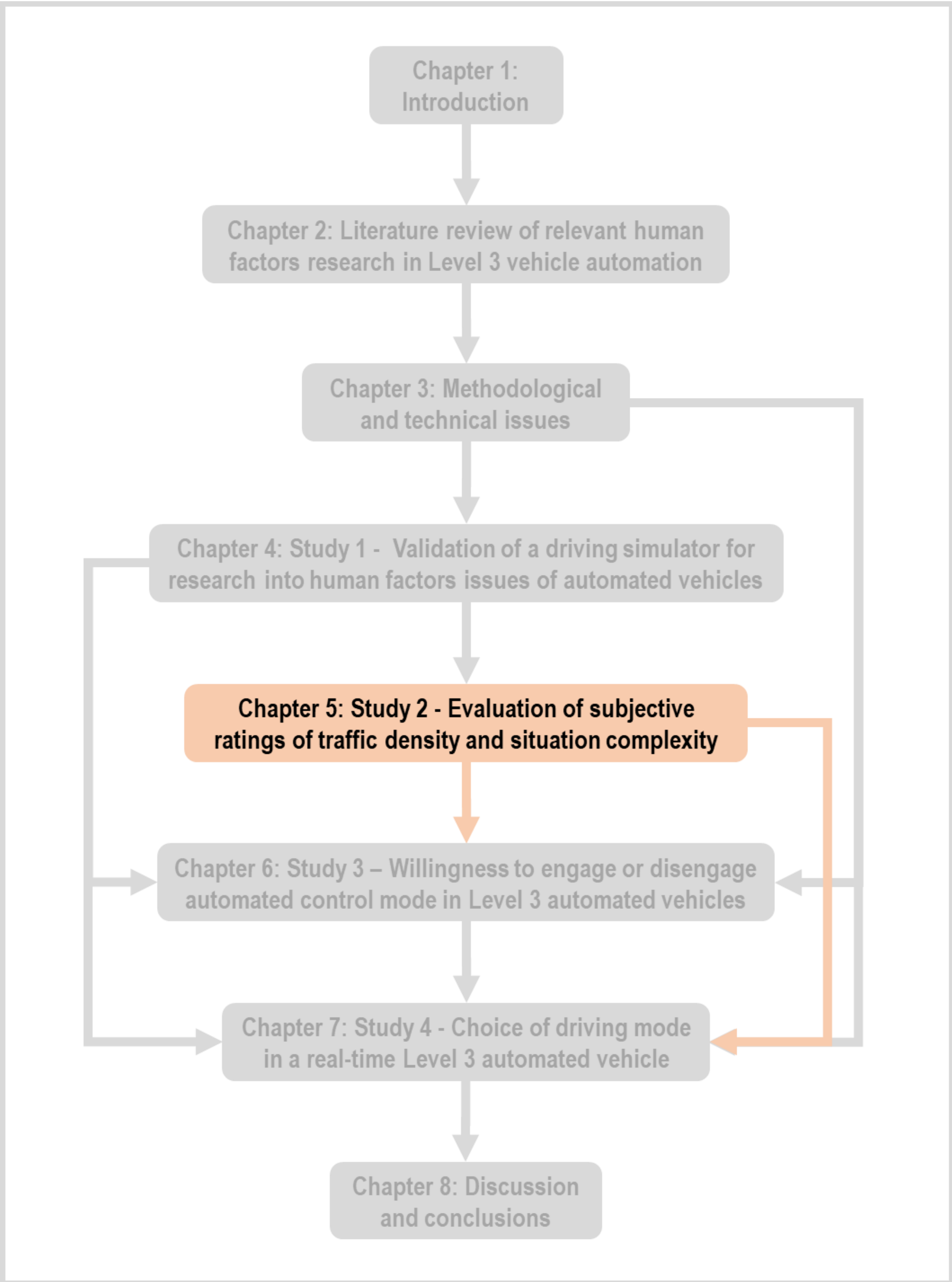
The results confirmed the relative behavioural validity of the newly-built MUARC automated driving simulator. It can be argued that if the limitations of the study discussed in previous sections are properly addressed, even absolute behavioural validity could be confirmed. The small number of statistical differences in subjective WTE and POS ratings observed during the validation study was largely the result of a failure to adequately replicate critical features of on-road events and conditions in the simulator. Blana (1996) compared several simulator validation studies and concluded that a carefully designed experimental procedure is an important element for the success of a behavioural validation study. These findings were used for the design of future simulator experiments investigating WTE/WTRC and the associated POS.

The following guidelines should be followed in the design of the simulator scenarios for research of human factors issues in automated driving for both current research and other similar studies:

- If possible, scenarios should contain a type of events that are likely to produce similar driver behaviour between on-road and simulator drives
- Very high-risk or high-stakes situations should be avoided in the scenario
- Physical validity limitations of the simulator should be considered (restricted FOV, representation of acceleration, absolute speed validity) and events that require cues the simulator is not able to provide, avoided.
- Enough time should be given to participants between events to allow immersion into the simulation and return to normal driving task state.

During processing and analysis of recorded question points, levels of TD (traffic density) and SC (situation complexity) were used to produce dependent variables. However, in the discussion of results, subjective perception of levels of TD and SC have been identified as a potential confounding factor contributing to differences in ratings of WTRC and POS. From the perspective of future research, it was judged that there was a need to further explore the metric of these categories. More specifically, it was important to better understand if there were differences in the subjective perception of TD and SC levels and what is the extent of these differences. These questions were addressed in the next chapter which describes Study 2.

CHAPTER 5


Chapter 1: Introduction
Chapter 2: Literature review of relevant human factors research in Level 3 vehicle automation
Chapter 3: Methodological and technical issues
Chapter 4: Study 1 - Validation of a driving simulator for research into human factors issues of automated vehicles
Chapter 5: Study 2 - Evaluation of subjective ratings of traffic density and situation complexity
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Chapter 7: Study 4 - Choice of driving mode in a real-time Level 3 automated vehicle
Chapter 8: Discussion and conclusions

Chapter 5 Study 2: Evaluation of Subjective Ratings of Traffic Density and Situation Complexity

5.1 Introduction

5.1.1 Background

During the validation of the driving simulator (presented in Chapter 4), the results of the data analysis suggested that subjective difference in how driving situations were perceived between participants, in terms of TD (traffic density) and SC (situation complexity), had an effect on drivers' WTRC and POS in a Level 3 automated vehicle.

While driving situations can be measured in terms of physical characteristics, subjective perception of the level of TD and SC depends on individual driver processes (cognitive, motivational and energetic) as defined by the JCTF model (Wege et al., 2013). For example, a medium complexity event could have been perceived as high complexity event by one group of participants, and as low complexity event by another group of participants. These differences are likely to influence the WTE (driver's willingness to engage vehicle automation).

Therefore, a study that would observe and explore magnitudes of differences in subjective perceptions of TD and SC was deemed important for the design of the future driving simulator studies in this research program. This chapter presents a laboratory study conducted to evaluate differences in subjective perceptions of levels of TD and SC of variety of every day driving situations.

5.1.2 Effects of traffic density and situation complexity on driver behaviour

The effects of SC and TD on driving behaviour have been investigated by human factors researchers in the past, with both SC and TD been recognised as contributors to the level of driving task demands. Significant effects of TD on driver performance have been found in on-road studies such as Antin et al. (1990), Zeitlin, (1993) and Verwey (2000), with findings indicating a positive correlation between subjective driving task difficulty and TD. Hao et al. (2007) found an increase in mental workload as a result of an increase in traffic in their simulator study. Teh et al. (2014) found that driver self-reported workload increased with increase in TD. Jamson et al. (2013) observed the effect of TD in the context of automated driving and found that safety margins associated with car following were reduced in heavy traffic. A similar effect was reported by Yang et al. (2018) who examined the effect of TD on drivers' lane change and overtaking manoeuvres. They observed an increase in the number in of overtaking manoeuvres and lane changes as well as an increase in vehicle acceleration during these actions as a result of the increase in TD.

Similar effects were reported for SC. In their study, de Craen et al. (2008) measured speed adaptation in response to the level of complexity and found that the complexity had a negative effect on driving speed. Oviedo-Trespalacios et al. (2017), in their simulator study on effects of road infrastructure and traffic complexity on speed adaptation behaviour of distracted drivers, observed that road and traffic complexity played an important role in the decision-making process of distracted drivers in speed adaptation. In their review of empirical studies, Paxion et al. (2014a) attempted to understand how the subjective and objective levels of mental workload influence the performance as a function of SC and driving experience. They concluded that studies confirm the positive relationship between the SC and the physiological measures correlated to mental workload. Increased SC also leads to performance degradations. Paxion et al. (2014b) used different levels of SC to investigate the effects of physiological and subjective levels of tension on driving performance, showing the difference between novice and experienced drives. More recently, Cabrall and Winter, (2017) too found that the complexity factor corresponded to the subjective effort. Faure et al. (2016) manipulated driving task difficulty by varying complexity of the simulated driving environment and with results confirming an increase in driver's mental work with an increase in the complexity of the driving environment. Therefore, it can be concluded that SC and TD have a strong effect on driving task workload and driver behaviour.

5.1.3 Aims

The aims of the study were to assess the variability of subjective judgements of traffic density and situation complexity and to establish a relative scale of situation complexity for subsequent simulator studies. This was an exploratory study and, as such, no hypotheses were formulated. The practical goal of this study was to find a solution for circumventing possible confounding effects of differences in the subjective perception of TD and SC between participants in the next two simulator studies.

5.2 Method

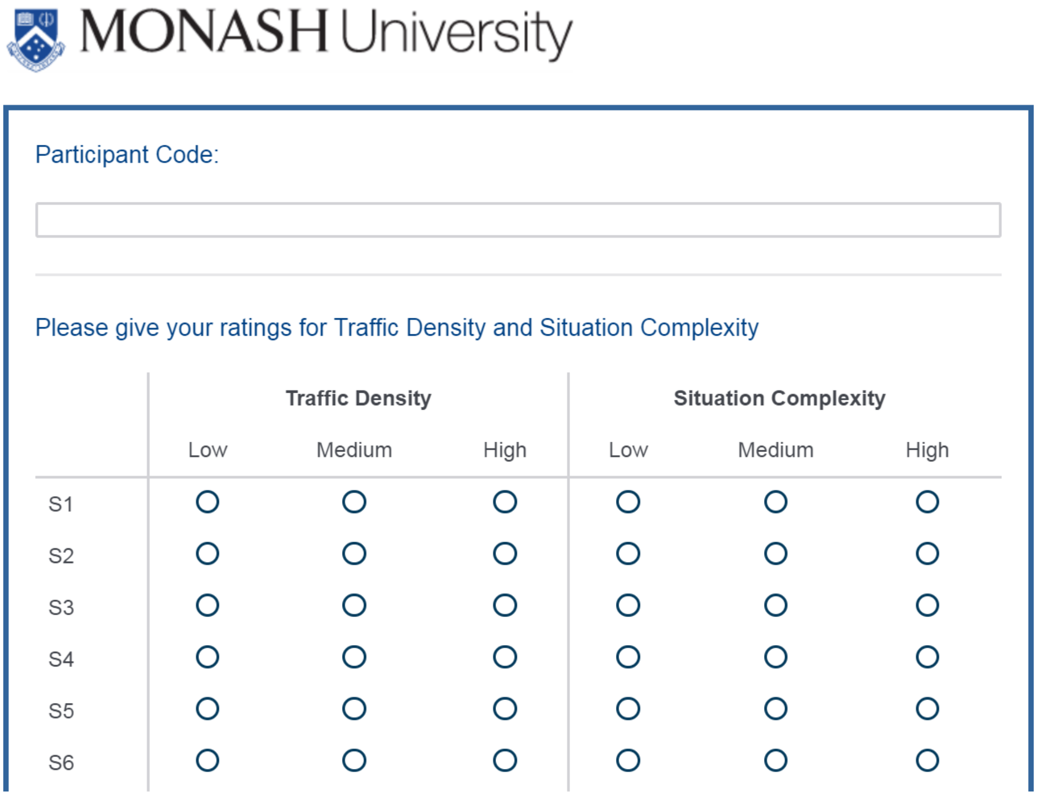
5.2.1 Participants

Twenty participants completed the study: 12 males and 8 females. The average age across all participants was 37.4 years (range 20 to 73, standard deviation 13.6). They held their driver licence for 16.7 years on average (range 2 to 55, standard deviation 13.6). Participants were recruited from both Monash University (undergraduate students, post-graduate students and staff) and outside using personal contacts, MUARC participant database and advertising on social media. Participants were required to have either a full driver licence or second-year probationary licence. They were also required to drive at least 5,000 km per year.

5.2.2 Apparatus

This study was conducted in a laboratory using two PCs, one to play video clips and the second to record participant responses. A total of 48 video clips were presented to each participant on 24" monitor. Each video clip lasted between five and ten seconds and presented one driving situation. Video clips were recorded in the simulator and on-road. They represented a range of every day driving situations varying in both traffic density and situation complexity. They ranged from very simple situations such as driving on a straight road with no other road users present, to situations that involved multiple road users and complex maneuvering such as merging on a freeway or entering a busy intersection. However, no safety-critical or very risky situations were included in the presented set of video clips. Screen captures of a driving situation, on-road and simulator, are illustrated in **Figure 5.1**. Participant responses were recorded using an electronic questionnaire. Qualtrics survey software was used for the development and administration of questionnaires. An example of a questionnaire item is shown in **Figure 5.2**.

Figure 5.1 *Screen capture of **a)** on-road video clip , and **b)** equivalent simulator video clip*



MONASH University

Participant Code:

Please give your ratings for Traffic Density and Situation Complexity

	Traffic Density			Situation Complexity		
	Low	Medium	High	Low	Medium	High
S1	O	O	O	O	O	O
S2	O	O	O	O	O	O
S3	O	O	O	O	O	O
S4	O	O	O	O	O	O
S5	O	O	O	O	O	O
S6	O	O	O	O	O	O

Figure 5.2 *Example of Traffic density and Situation Complexity questionnaire*

5.2.3 Procedure

Upon arrival, participants read the experiment summary and completed an informed consent form, as approved by the Monash University Ethics Committee. This was followed by a short demographic questionnaire. Before the start of the experimental task, participants were given instructions on how to enter their ratings in the questionnaire. No specific suggestions on how to rate TD or SC were provided. Instead, participants were encouraged to give their subjective ratings based on their driving experiences and attitudes. After each video clip was played, participants were required to enter their subjective ratings for TD (traffic density) and SC (situation complexity). Both TD and SC were presented in the form of multiple-choice questions with three possible answers being Low, Medium and High for each category. Low rating was scored as 1, medium rating as 2 and high rating as 3. Before the start of the experimental task, a practice clip was played and participants were asked to rate clip in terms of TD and SC. After participant demonstrated understanding of the experimental task the questionnaire started and the first video clip was played. When ratings for both TD and SC were entered the questionnaire progressed to the next question and the new video clip was played. This procedure was repeated for all 48 video clips. Simulator clips were presented first followed by on-road clips. The duration of the experimental session was about 15 minutes. The experimental procedure is illustrated in **Figure 5.3**.

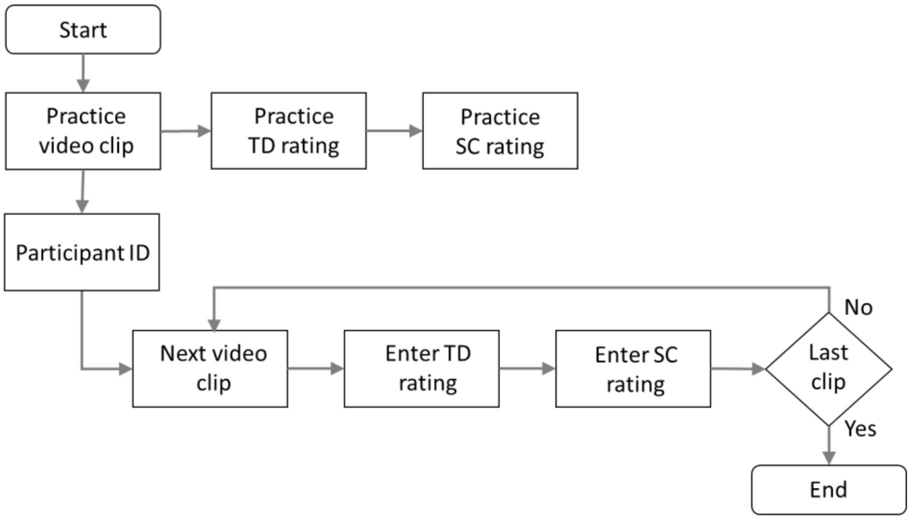


Figure 5.3 *Flowchart illustration of Study 2 experimental procedure*

5.3 Results

5.3.1 Means of traffic density and situation complexity for each video clip situation

A summary of descriptive statistical results is presented in **Table 5.1**. All clip IDs with prefix S refer to simulator drive clips while prefix R refers to on-road drive clip. The overall mean TD rating for simulator driving clips was 1.354 on the scale from 1 to 3, while the overall mean TD rating for on-road driving clips was 1.567 (15.68% higher than simulator ratings) on the same scale. The lowest Mean TD score of 1.00 was observed for 7 clips (3 in the simulator drive, 4 in the on-road drive). The highest Mean TD score of 2.25 in simulator drives was observed for clip S15 (Freeway congestion – changing lanes) while the highest score for a clip from on-road drives was 2.90 (R6 - Slow traffic congestion).

Using the same scale from 1 to 3, the overall mean SC rating for simulator video clips was 1.621, while the overall mean SC rating for on-road driving clips was 1.617 (0.26% lower than simulator ratings). The lowest Mean SC score in the simulator drive was 1.05 observed for clips S1 and S13 (Free driving) and 1.00 for clip R12 (Free driving) from the on-road drive. The highest mean SC score of 2.60 for the simulator situations was 2.60 for the clip S20 (Freeway congestion - changing lanes) and 2.20 for the clip R19 (Give way) for the on-road situations.

Table 5.1 *Means and standard deviations of TD and SC for each video clip*

Clip ID	Description of video clip	Mean TD	SD TD	Mean SC	SD SC
S1	Free driving	1.00	0.00	1.05	0.22
S2	Amber lights and pedestrian	1.05	0.22	1.85	0.59
S3	Pedestrian crossing – red lights	1.90	0.55	1.40	0.60
S4	Left bend	1.15	0.37	1.20	0.52
S5	Roundabout	1.20	0.41	1.90	0.64
S6	Following cyclist	1.55	0.61	2.00	0.73
S7	Green light and parked cars	1.65	0.59	1.20	0.41
S8	Flashing traffic lights – behind bus	1.30	0.47	1.95	0.61
S9	Turning left - road obstruction	1.25	0.44	1.70	0.57
S10	Merging onto freeway - clear	1.15	0.37	1.75	0.64
S11	Vehicle following	1.35	0.49	1.75	0.79
S12	Overtaking truck – changing lanes	1.20	0.41	1.65	0.49
S13	Free driving	1.15	0.37	1.05	0.22
S14	Free driving	1.05	0.22	1.10	0.31
S15	Freeway congestion – changing lanes	2.25	0.64	2.55	0.51
S16	Freeway exit	1.65	0.59	1.30	0.47
S17	Stop sign (low visibility)	1.00	0.00	1.70	0.66
S18	Stopped bus and pedestrians	1.45	0.51	2.00	0.80
S19	Right bend - ramp	1.00	0.00	1.35	0.49
S20	Freeway congestion - changing lanes	2.20	0.70	2.60	0.50
S21	Right bend	1.05	0.22	1.25	0.55
S22	Changing lanes on freeway	1.80	0.62	2.20	0.77
S23	Left bend - ramp	1.10	0.31	1.10	0.31
S24	Right bend - ramp	1.05	0.22	1.30	0.57
S	**All simulator clips**	**1.354**	**0.562**	**1.621**	**0.706**
R1	Green light	1.00	0.00	1.50	0.51
R2	Roundabout	1.10	0.31	1.65	0.59
R3	Give way intersection	1.25	0.44	1.60	0.60
R4	Following cyclist	1.30	0.47	1.95	0.61
R5	Approaching stopped cars	1.20	0.41	1.90	0.72
R6	Slow traffic congestion	2.90	0.31	1.45	0.61
R7	Free driving on freeway	2.40	0.60	1.80	0.70
R8	Merging traffic	2.30	0.47	1.90	0.64
R9	Free driving	1.35	0.49	1.20	0.41
R10	Vehicle following	1.40	0.50	1.40	0.50
R11	Changing lanes	1.45	0.51	1.40	0.50
R12	Free driving (left bend)	1.00	0.00	1.00	0.00
R13	Merging	1.60	0.50	1.90	0.55
R14	Free driving	1.00	0.00	1.10	0.31
R15	Roundabout	1.50	0.61	1.80	0.70
R16	Pedestrian and oncoming cars	1.30	0.47	1.80	0.52
R17	Approaching stopped cars/pedestrian	1.95	0.39	1.75	0.72
R18	Car exiting parking	1.10	0.31	1.25	0.44
R19	Give way	2.60	0.50	2.20	0.62
R20	Stopped bus	2.10	0.55	1.80	0.52
R21	Right bend – ramp	1.55	0.51	1.30	0.57
R22	Freeway merging	2.10	0.45	1.65	0.67
R23	Merging onto arterial road	1.15	0.37	1.75	0.55
R24	Pedestrian crossing/flashing lights	1.00	0.00	1.75	0.44
R All	**All on-road clips**	**1.568**	**0.686**	**1.617**	**0.622**

5.3.2 Ratings of traffic density

The assessment of the difference in perceived levels of TD between participants was conducted using the Kappa Measure of Agreement statistics. Kappa is an estimate of the proportion of agreement between the two raters that takes into account the amount of agreement that could have occurred by chance. Standardised values of Kappa lie on a -1 to 1 scale, where 1 is the perfect agreement, 0 is exactly what would be expected by chance, and negative values indicate agreement less than chance (Viera and Garrett, 2005). For example, a potential systematic disagreement between the observers would result in a negative Kappa.

Kappa tests were conducted on all combinations of pairs of raters. In total, 190 combinations of pairs of raters were compared. Due to a large number of tests, the results are summarized in the form of a heat map (**Table 5.2**). Colours of each field in the table correspond to the value of Kappa Measure of Agreement.

Table 5.2 *Traffic Density Kappa heat map*

	P01	P02	P03	P04	P05	P06	P07	P08	P09	P10	P11	P12	P13	P14	P15	P16	P17	P18	P19	P20
P01		0.13	0.49	0.29	0.35	0.00	0.18	0.11	0.24	0.27	0.53	0.42	0.14	0.33	0.41	0.45	0.43	0.08	0.60	0.20
P02			0.30	0.24	0.49	0.64	0.64	0.70	0.74	0.54	0.21	0.09	0.66	0.64	0.38	0.27	0.34	0.69	0.33	0.90
P03				0.25	0.36	0.12	0.31	0.17	0.35	0.22	0.33	0.29	0.30	0.41	0.39	0.37	0.15	0.20	0.31	0.31
P04					0.40	0.23	0.46	0.23	0.22	0.22	0.53	0.42	0.18	0.27	0.37	0.51	0.37	0.41	0.21	0.36
P05						0.29	0.46	0.43	0.46	0.49	0.46	0.13	0.54	0.53	0.40	0.32	0.37	0.33	0.51	0.58
P06							0.55	0.53	0.49	0.31	0.15	0.05	0.53	0.38	0.31	0.16	0.16	0.48	0.13	0.54
P07								0.55	0.60	0.52	0.37	0.26	0.63	0.48	0.52	0.32	0.36	0.40	0.25	0.65
P08									0.66	0.40	0.20	0.14	0.59	0.39	0.23	0.13	0.29	0.71	0.25	0.60
P09										0.43	0.19	0.22	0.72	0.61	0.52	0.24	0.36	0.64	0.32	0.65
P10											0.28	0.21	0.58	0.42	0.44	0.22	0.49	0.31	0.47	0.55
P11												0.31	0.18	0.42	0.41	0.59	0.45	0.11	0.44	0.29
P12													0.08	0.26	0.21	0.38	0.10	0.12	0.20	0.18
P13														0.53	0.48	0.10	0.35	0.46	0.33	0.57
P14															0.51	0.27	0.38	0.42	0.40	0.74
P15																0.40	0.47	0.22	0.34	0.39
P16																	0.45	0.15	0.27	0.35
P17																		0.24	0.50	0.43
P18																			0.19	0.58
P19																				0.34
P20																				

The colour scheme used in this table is derived from guidelines by Peat et al. (2001) and explained in **Table 5.3**. The displayed colour scale is presented as a gradient, ranging from red, representing no agreement (0.00) to green, representing a very good agreement (≥ 0.80). The orange colour represents a fair agreement (0.30).

Table 5.3 *Colour scheme for interpretation of Kappa measures of agreement*

Agreement level	Kappa value	Cell colour
No agreement	0.00	
Poor agreement	0.10	
Fair agreement	0.30	
Moderate	0.50	
Good	0.70	
Very good	> 0.80	

In addition to standard Kappa tests a Fleiss Kappa test was conducted. The Fleiss Kappa is a version of the test for 3 or more raters. The interrater reliability for the raters and across all 48 clips was found to be *Fleiss Kappa* = .36 (p < .001, 95% *CI* (.34, .37).

5.3.3 Ratings of situation complexity

Similarly, the difference in perceived levels of SC between participants was assessed with the Kappa Measure of Agreement statistics. As with ratings of TD, Kappa tests were conducted on all combinations of pairs of raters. In total, 190 combinations of pairs of raters were compared. The results are summarized in the form of a heat map (**Table 5.4**). Colours of each field in the table correspond to the value of Kappa Measure of Agreement according to **Table 5.3**. The Fleiss Kappa test interrater reliability for all of the raters and across all 48 clips was found to be *Fleiss Kappa* = .19 ($p < .001$), 95% *CI* (.17, .21).

Table 5.4 *Situation Complexity Kappa heat map*

	P01	P02	P03	P04	P05	P06	P07	P08	P09	P10	P11	P12	P13	P14	P15	P16	P17	P18	P19	P20
P01		0.11	0.07	-.022	0.16	0.03	0.20	0.09	0.23	0.30	0.01	0.31	0.11	0.13	0.29	0.15	0.25	0.07	0.11	0.19
P02			0.37	0.22	0.28	0.25	0.35	0.18	0.41	0.30	0.18	0.27	0.17	0.15	0.48	0.25	0.25	0.20	0.20	0.35
P03				0.00	0.15	0.09	0.08	0.04	0.26	0.08	0.10	0.00	0.15	0.27	0.25	0.32	0.34	0.11	0.03	0.15
P04					0.25	0.28	0.44	0.10	0.10	0.21	0.20	0.07	-.033	0.06	0.10	0.15	-.076	0.32	0.19	0.03
P05						0.46	0.35	0.08	0.17	0.25	0.19	0.02	0.29	0.08	0.37	0.08	0.02	0.33	0.12	0.16
P06							0.21	0.11	0.09	0.16	0.12	-.016	0.07	0.03	0.26	0.23	0.12	0.19	0.26	0.09
P07								0.19	0.30	0.46	0.14	0.08	0.26	0.06	0.29	0.07	0.13	0.42	0.08	0.28
P08									0.17	0.21	0.18	0.15	0.19	0.42	0.21	0.12	0.07	0.16	0.01	-.026
P09										0.53	0.26	0.42	0.25	0.21	0.47	0.35	0.41	0.21	0.32	0.40
P10											0.14	0.32	0.39	0.14	0.50	0.12	0.24	0.40	0.14	0.20
P11												0.15	0.10	0.17	0.23	0.21	0.09	0.13	0.24	0.28
P12													0.08	0.05	0.32	0.22	0.11	0.00	0.10	0.43
P13														0.25	0.21	0.19	0.10	0.23	0.00	0.18
P14															0.13	0.24	0.25	0.26	0.01	0.01
P15																0.20	0.41	0.21	0.29	0.36
P16																	0.36	-.007	0.32	0.25
P17																		0.16	0.27	0.45
P18																			0.08	0.11
P19																				0.11
P20																				

5.4 Discussion

The results of the statistical analysis suggest that SC was harder to rate than TD. Visual inspection of Kappa heat maps suggested that overall agreement between raters was fair for levels of TD and poor for levels of SC. This observation was confirmed by Fleiss Kappa scores. This is not surprising since TD, unlike SC, has a potential to be objectively quantified (e.g. count of all vehicles in the scene) despite any differences in the subjective perception of TD. However, although achieving better agreement then SC, the level of agreement on levels of TD was relatively low. Without precise instructions on how to determine levels of TD being given to participants, there was a scope for variability in the estimation of TD levels. For example, participants could have been given guidance such as that no vehicles in the scene should be scored as low TD, between 1 and 3 as medium TD and more than 3 as high TD. Since such, objective scale was not provided, participants used their subjective metrics, resulting in fair agreement.

The poor agreement on levels of SC is likely to be related to individual driver skillset and experience. For example, driving on icy roads may not appear as very complex until it is experienced. Alternatively, drivers who are familiar with a certain driving situation may perceive it as less complex than unfamiliar drivers. The aim of this study was not an analysis of factors that contribute to SC; however visual stimulation was considered to be critical especially in the driving simulator. Edquist (2008) suggested that visual clutter has the potential to capture the driver's attentional resources and impair driving performance particularly in the case of older drivers. Three types of visual clutter were identified as situational clutter (all moving objects on or next to the road), designed clutter (signage), road markings and built (infrastructure) clutter. Even if the rated event is very simple, raters might subjectively identify certain complex features that in reality, do not contribute to the overall complexity. Unless an experimental scenario is completely sterilised of all non-essential visual features, specifically in a form of designed clutter and built clutter (Edquist, 2008), there is always a possibility for diversity of interpretations. However, comparisons of mean ratings of SC for each video clip demonstrated that basic situations such as Free driving were almost uniformly perceived as distinctively less complex than events such as Give way, Vehicle following or interactions with vulnerable road users such as pedestrians or cyclists. Therefore, it was concluded that if the difference in objective complexity of two driving situations is sufficiently large, the effect of subjective perception of complexity is likely to be absorbed within subjective complexity.

The order of video clips presented to participants was not randomised and as a result, there is a possibility of certain order effects. Although it is anticipated that order events did not have a large impact on behaviour, future studies should randomise such order.

5.5 Conclusions

5.5.1 Recommendations for future research

Although the fundamental goal of this study has been successfully achieved, future research could explore the correlation of subjective perception of TD and SC and demographics categories such as age and driving experience. A possible correlation could be universally used in human factors research of driving, including vehicle automation. Additionally, a set of standardised driving situations could be defined for use in driving simulator studies. The results obtained in these standardised situations would have the potential to be comparable, at some level, across different simulator studies.

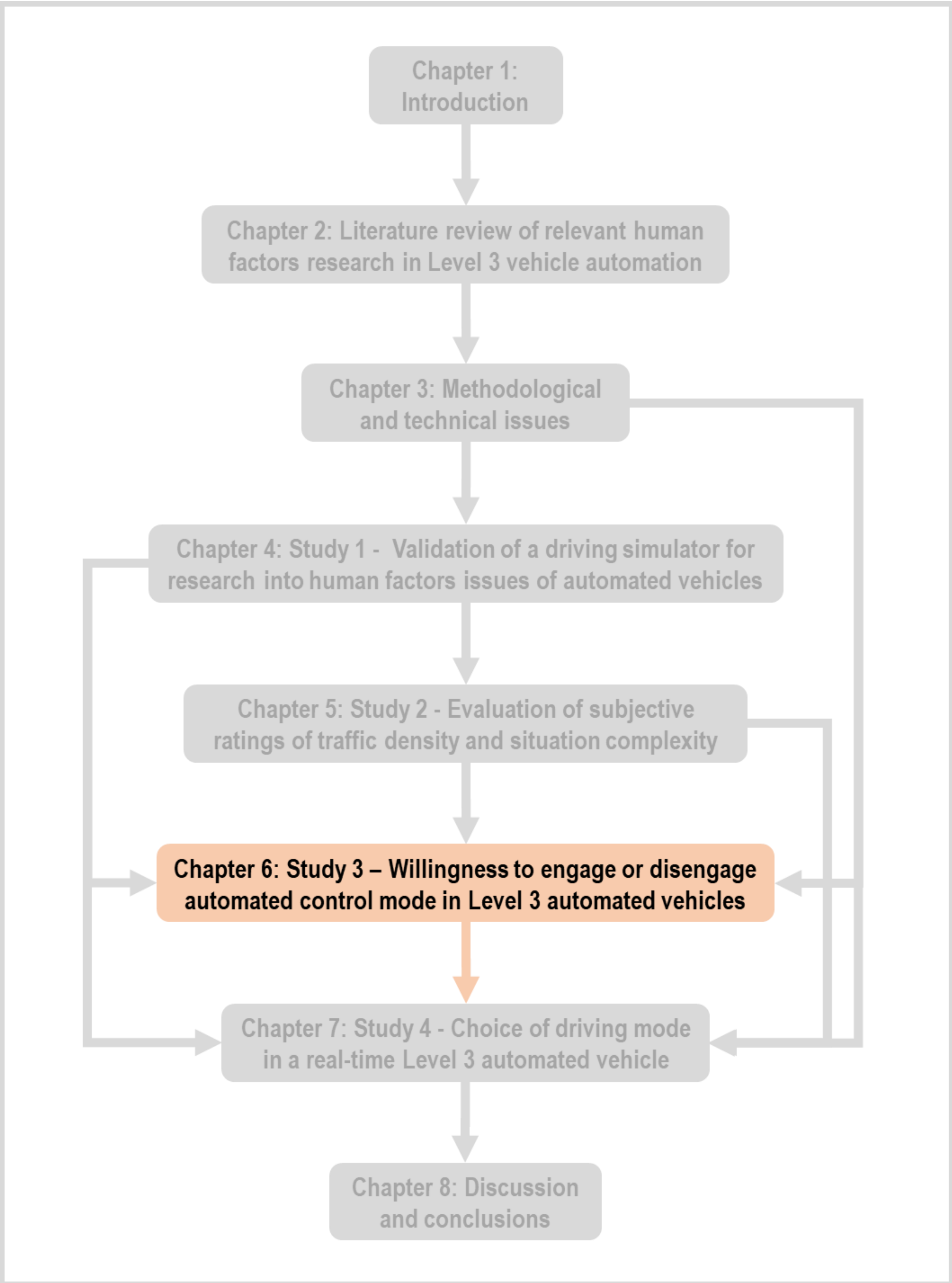
5.5.2 Guidelines for future studies

As a result of data analysis and evidence found in the literature, guidelines for the design of future simulator studies that may exploit different levels of TD and SC as independent variables were formulated. The first guideline refers to the contrast between levels of TD and SC. When designing the simulator scenario, it is important to present driving situations with a substantially large and easily identifiable difference between low and high levels of SC and TD. This is critical in the case of the SC since the levels of agreement were lower and therefore the risk of failure to achieve the desired effect is increased. This issue was observed by Paxion et al. (2014b) who used three levels of SC in their study and found that moderately complex situation did not sufficiently differ from the other two levels to obtain different levels of objective effects and by Eriksson (2014) finding that complexity had a threshold effect on decision-making time in automated vehicle. In their recent study Perello-March et al. (2021) reported difficulty in differentiating observable differences in driver physiology between moderate and other levels of complexity during automated driving. They suggested use of more dramatic scenarios to induce observable physiological responses in drivers.

Secondly, scenario events should be devoid of any possible confounding or contaminating factors in the form of visual clutter, unnecessary conspicuous objects or any actions that may distract from the objective. For example, an event that involves certain hazardous behaviour by a pedestrian should not involve other actions or objects that may compete for the participant's attention. A similar recommendation was made by Diels et al. (2015) who concluded that it is undesirable to induce unnecessary additional mental workload in the simulator. Also, it has been decided that only SC would be used as an independent variable in future studies. In their investigation of the relationship between dynamic traffic behaviour factors and subjective workload, Teh et al. (2014) stated that TD was a factor of traffic complexity. In other words, TD can be considered as a contributor to SC. Furthermore, it is generally easier to design and develop a simulator scenario event that consists of a smaller number of active objects (e.g. vehicles and pedestrians) present in the scene.

These guidelines were followed in the design of the simulator studies presented in the next two chapters. Therefore, in both simulator studies, SC was introduced as an independent variable with two levels presented: low SC and high SC. All presented driving situations were free, as much as possible, of potential visual distractions from the main task.

CHAPTER 6



Chapter 1: Introduction
Chapter 2: Literature review of relevant human factors research in Level 3 vehicle automation
Chapter 3: Methodological and technical issues
Chapter 4: Study 1 - Validation of a driving simulator for research into human factors issues of automated vehicles
Chapter 5: Study 2 - Evaluation of subjective ratings of traffic density and situation complexity
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Chapter 6 Study 3: Willingness to engage or disengage automated control mode in Level 3 automated vehicle

6.1 Introduction

This study examined drivers' WTE (willingness to engage automated driving mode) and WTRC (willingness to resume manual control) of a Level 3 automated vehicle and factors that influence this decision.

6.1.1 Background

Level 3 vehicle automation is on the verge of becoming mainstream from a technological point of view. As it keeps developing and becoming more accessible it could likely follow the path of the anti-lock braking system (ABS) (ADR, 2017b) and electronic stability control (ESC) (ADR, 2017a). These technologies became mandatory in 2003 and 2013, respectively, for all new cars sold in Australia after the effectiveness of these technologies was demonstrated on roads. For example, researchers used real-life crashes data in their analysis and found that ESC significantly reduced crashes and injuries (Erke, 2008; Lie et al., 2006; Scully & Newstead, 2007). Similar results were reported in UK research that indicated that equipping a vehicle with ESC reduced the risk of being involved in a fatal crash by 25% (Frampton & Thomas, 2007). Kahane and Dang (2009), and Burton et al. (2004) reported the effectiveness of ABS, especially in non-fatal crashes. Kahane and Dang (2009) concluded that the combination of ESC and ABS prevented a large proportion of fatal and non-fatal crashes. Fitzharris et al. (2010) estimated significant benefits of ESC fitment to light commercial vehicles. Once the safety benefits of Level 3 vehicle automation are confirmed, the adoption path similar to those of ABS and ESC may be followed.

Therefore, this research was conducted under the assumption that in the foreseeable future, all new vehicles would have Level 3 automation capability, mostly because this technology would become an affordable part of standard vehicle kit. Under this scenario, all drivers of new vehicles would be able to choose vehicle control mode, even if vehicle automation was not an important feature for some drivers. There is still a significant gap between the available level of automated driving technology and current regulations that are preventing the legalisation of Level 3 automated vehicles. Crossing this final hurdle requires a better understanding of how automated vehicles will be used and identifying all possible issues and problems with it. This research aimed to contribute to that knowledge.

As described in Chapters 1 and 2, some of the commonly researched topics related to automated vehicles were the transfer of control, benefits and disadvantages of AVs and behavioural adaptation to AVs (Merat & de Waard, 2014). The literature search identified a lack of simulator-based studies that exposed drivers to Level 3 AVs and investigated issues associated with everyday driving. In particular, there is a lack of research on the factors that influence a driver's use of vehicle automation.

Therefore, this study aimed to explore factors that may influence WTE and WTRC during non-critical driving. The factors that are likely to influence WTE are identified from the thesis literature review and in the adaptation of the JCTF, the theoretical framework of behavioural adaptations to ADAS, proposed by Wege et al. (2013), introduced in Chapter 2 of this thesis. In the course of the study, driver responses were explored by manipulating a range of conditions in the driving simulator scenarios that represented independent variables of the study.

Thus far in this research project, using a surrogate automated driving task, the utility of the driving simulator for conducting specific behavioural research on the human factors of automated vehicles was established. Also, the results of the validation study suggested that for the majority of participants, more demanding driving situations were likely to be associated with higher WTRC and lower WTE. Situation complexity, traffic density and driving speed were identified as some of the factors affecting the difficulty of driving task. Study 2 (Chapter 5) investigated agreement of subjective perception of situation complexity and traffic density and confirmed large variability of complexity ratings among participants. As a result of the findings from the first two studies, a set of guidelines for the design of Study 3 (Chapter 5) and the development of experimental scenarios were established.

6.1.2 Independent and dependent variables to be tested

The selection of independent variables was critical for the study design. The manipulation of independent variables intended to expose participants to a variety of situations that represented different levels of driving task demands. Fuller (2011) described driving as *"a control task in an unstable environment created by the driver's motion with respect to a defined track and stationary and moving objects"* (p. 13), stating that the difficulty of the driving task is inversely related to the discrepancy between the task demands and the driver's available capability. Therefore, the selection of independent variables had to allow for the presentation of a variety of driving task demands without exceeding the driver's available capability as the research was focussed on everyday driving.

The review of the literature revealed that a wide range of independent variables commonly used in the driving simulator or laboratory studies. Although speed was most frequently used as a dependent variable, variations in speed conditions have been used as an independent variable as well. For example, Fuller et al. (2008) used different speeds in the measurement of task difficulty and perceived risk, Fildes et al. (1989) for estimating perceived speed and safety. Favarò et al. (2019) used two different speed conditions in the examination of automation failures.

Frison et al. (2019) used variations of road type and traffic volume in the investigation of the perception of automation. Similarly, Dijksterhuis et al. (2011) exposed participants to narrow lane widths and high traffic density to determine changes in mental effort. Edquist et al. (2009) investigated the influence of various factors within the road environment on speed choice.

Vlakveld et al. (2015) used a variety of latent hazards in the exploration of situation awareness in the transition from automated to manual driving mode. They defined latent hazards as traffic situations that experienced and alert drivers recognize as situations that have a rather high likelihood to develop into acute threatening situations, despite their harmless appearance at first sight. TH (time headway) was also used in many studies such as Tscharn et al. (2018) who investigated the relationship between velocity and subjective risk of different THs in a driving simulator. Siebert et al. (2017) investigated the thresholds for subjective risk and comfort experience in car following. De Waard and Van der Hulst (1999) used different levels of TH as a condition in the exploration of platoon driving. Lewis-Evans, De Waard and Brookhuis (2010) used different THs in the exploration of task difficulty, risk, effort and comfort.

Situation complexity (SC) was also manipulated in studies that explored subjective workload (Paxion et al., 2014a) and in the investigation of in-vehicle display designs (Horrey & Wickens, 2004). De Craen et al. (2008) used different levels of traffic complexity to measure adaptation of driving speed. Horberry et al. (2006) used simple and complex road environments to investigate the effect of visual clutter. Oviedo-Trespalacios et al. (2017) used road infrastructure and traffic complexity in the exploration of speed adaptation of distracted drivers. Cabrall and Winter (2017) used the complexity of driving scenes to measure perceived effort.

The automation level was used as an independent variable by Jamson et al. (2013). A variety of other variables were manipulated in studies on automated driving, such as traffic density (Jamson et al., 2013) and exposure to critical events while driving in automated mode (Merat & Jamson, 2008).

The adapted JCTF (Joint Conceptual Theoretical Framework) identified factors that are likely to affect WTE. The limitations of the available driving simulator had to be taken into consideration too. If the simulator was not able to produce certain cues or some aspects of the simulation have not been validated, these cues or aspects should not be used as independent variables. Some of these limitations were identified during the validation process, such as lack of absolute perception of speed and restricted FOV (field of view) of the display system. The three external factors from the range of factors that influence WTE, as identified by the adapted theoretical framework and findings from previous research in the driving simulators, were found suitable for manipulation in experimental scenarios and selected as independent variables for the study. They were driving mode, situation complexity and driving speed. The driver characteristics and attitudes were assessed with a demographic questionnaire.

Driving mode

The driving mode (vehicle factor) was an important independent variable representing two experimental conditions, manual driving and automated driving. In Level 3 automation, the driver can choose between these two modes (SAE International, 2014), therefore both driving modes had to be presented to participants. For example, Stapel et al. (2019) evaluated subjective driver workload in manual and automated driving.

Situation complexity

The SC (situation complexity) was found to be highly correlated to driving task workload (Cantin et al., 2009; Paxion et al., 2014a), and therefore it was expected to have a significant effect on dependent variables. Similarly, Cabrall and de Winter (2017) concluded that the complexity of the driving scene corresponds to the subjective effort, while Stapel et al. (2019) found that perceived and objective workload increased with traffic complexity. With their study findings, Faure et al. (2016) confirmed that drivers' mental workload level increased with the complexity of the driving environment.

Following guidelines from the previous two studies, two distinctive levels of situation complexity were selected, low SC and high SC. These levels were presented in the form of five events in the simulator drive. One event represented low complexity and the other four events represented high complexity. It was anticipated that individual ratings of high complexity events would be different however, all four high complexity events had to be distinctively more complex than the low complexity event. To ensure this, the event with the lowest complexity rating observed recorded in Study 2, the Free (free driving) event, was selected to represent low complexity condition as driving task demands were minimal. Fastenmeier and Gstalter (2007) defined the free driving situation by having the free choice of lane and velocity not affected by other cars and comfortable time headway. Paxion, Galy and Berthelon (2013) used such an event as a simple situation in the simulator study of subjective workload and double and sharper curves with oncoming traffic as high complexity events. Fuller (2000) illustrated a low task demand situation as driving "*on a quiet motorway with a clear lane to the front and behind, dry road surface and clear visibility*" (p. 2). Using perceived differences between these levels of complexity as a reference and examples from the literature, four events were selected to represent high SC in the study. They were Rain and Fog (RF), Oncoming car (OC), Give Way (GW) and Vehicle following (VF). These four high complexity events represented a wide variety of situations instead of relying on different levels of complexity of a single event. However, each of these four events made the driving task more demanding in comparison with the low complexity event. This is supported by the results of study 2 and examples of high task demand situations given by Fuller (2000). He listed negotiating bends, reduced visibility due to rain or dusk and the slower car ahead as such situations. The Free event, the GW event and the VF events were rated in Study 2. Both GW (give way) and VF (vehicle following) events were rated as significantly more complex than the free driving event.

The GW event forced the participant (driver) to make a gap-acceptance decision at an unsignalised intersection. The driver had to decide when to enter the intersection as there were multiple opportunities presented. The VF event aimed to expose participants to a borderline short time headway situation and therefore increased driving task demands. Lewis-Evans et al. (2010) found a mean threshold between risky and comfortable TH (time headway) in simulated driving to be between 1.5 and 2.0 seconds. This finding was also confirmed by Siebert et al. (2017). Therefore, TH was set to 1.5 seconds to increase the driver's perception of risk without making the driving task appear unrealistic or too uncomfortable. The same TH was used by Jamson et al. (2013) in the simulator study of behavioural changes in a highly automated vehicle. In this event, the driver was forced to actively monitor the headway and be vigilant regarding potential sudden braking by the lead vehicle while controlling the simulator car both longitudinally and laterally. The RF (rain and fog) event aimed to expose the driver to low visibility and deteriorated driving conditions. Fog is recognised as one of the most dangerous conditions for drivers (Saffarian, Happee, et al., 2012). Several studies confirmed that such conditions contributed to the increase in driving task demands. Farber and Gallagher (1972) used a similar approach in degraded visibility conditions to increase driving task difficulty. In their simulator study, Jeihani and Banerjee (2018) observed a significant reduction in speed due to the onset of fog, confirming an increase in driving task workload as a result of new road conditions. Hoogendoorn et al. (2011) found that mental workload increased significantly in reaction to fog. The purpose of the OC (oncoming car) event was to expose participants to a latent hazard that never materialised. Vlakveld et al. (2015) defined latent hazards as traffic situations that experienced and alert drivers recognize as situations that have a rather high likelihood to develop into acute threatening situations, despite their harmless appearance at first sight. The driver faced a potentially safety-critical event, simultaneously observing other vehicle and processing conflicting information (e.g. despite safe overtaking not being possible in the current situation, the oncoming vehicle has signalised intention to overtake). The driver needed to consider the possibility that the overtaking car could start unsafe manoeuvre before it is safe to do so.

Driving speed

The third independent variable was speed. As stated before, the driving simulator has not been validated for the absolute perception of speed. However, relative speed in simulators is recognised as an important dependent variable even if absolute speed validity was not established (Godley et al., 2002). The speed was also used as an independent variable in driving simulator studies such as Fuller et al. (2008). Studies on the adaptation of driving speed such as de Craen et al. (2008), de Waard et al. (2009) reported lower speeds as a response to increasing driving task demands. Hence, it can be concluded that higher driving speed was associated with an increase in driving task demands.

Dependent variables

Two dependent variables, previously used in Study 1, were recorded during the experimental drives: WTE (willingness to engage automated driving) during manual drives or WTRC (willingness to resume manual control) during automated drives and the perception of safety (POS) during all drives. Both dependent variables were subjective and self-reported with a questionnaire. WTE/WTRC directly investigated the main research question, while POS provided an insight into driver processes. POS was known to have an important influence on driving behaviour (Fildes, et al., 1989a, 1989b; Wang et al., 2002)

Driver characteristics are an integral part of the adapted JCTF and may provide additional insight into how WTE/WTRC was affected by demographics factors and attitudes such as confidence in own driving skills, perception of being a safe driver, driving enjoyment, attitude towards technology in cars, trust in automation and adoption of new technologies.

6.1.3 Research questions of the study

Building on findings from Studies 1 and 2, a simulator study to explore WTE/WTRC and POS under variable conditions was conducted. The variable conditions created various levels of driving task demands in non-critical situations.

The study aimed to answer the following research questions:

- How does a driver's WTE (willingness to engage automated control) or WTRC (willingness to resume manual vehicle control) change when exposed to the range of driving situations with different levels of complexity and different levels of driving task demands?
- If, and how, a driver's POS (perception of safety) changes in both driving modes (automated and manual) when exposed to driving situations with different levels of complexity and different levels of driving task demands?
- What are the key factors from driver characteristics that are influencing driver' WTE/WTRC and POS?

6.1.4 Hypotheses

Building on the research questions presented above, a series of hypotheses were formulated. The main hypotheses for this study are summarised in **Table 6.1**.

Table 6.1 *List of hypotheses for Study 3*

H#	Hypothesis
H6.1	Increase in SC has a negative effect on the WTE (willingness to engage automation and a positive effect on WTRC (willingness to resume control)
H6.2	The higher driving speed has a negative effect on WTE and a positive effect on WTRC
H6.3	Increase in SC has a negative effect on the POS (perception of safety)
H6.4	The automated driving mode has a positive effect on the POS
H6.5	Increase in driving speed has a negative effect on the POS
H6.6	The engaged driving mode has an effect on the preference of a driving mode
H6.7	Higher POS is negatively associated with WTE and positively associated with WTRC
H6.8	Driver characteristics and attitudes can be used as predictors of overall WTE/WTRC

6.2 Method

6.2.1 Experimental design

The study used a 2 x 2 x 2 factorial design (**Table 6.2**). The independent variables were speed (low/high), driving mode (manual/automated) and situation complexity (low/high). Dependent variables were WTE (willingness to engage automation) or WTRC (willingness to resume manual control) and POS (perception of safety).

Table 6.2 Study 3 factors

Factors (IVs)	Conditions
Speed	Low/High
Driving mode	Manual/Automated
Situation complexity	Low/High

The experiment used the simulation freeze technique. During each freeze of the simulation, participants were asked to complete a questionnaire item. The use of this technique has been reported in several simulation studies such as measurement of situation awareness during the takeover performance in automation (Endsley & Kiris, 1995) and use of adaptive cruise control system (Ma & Kaber, 2005). Although simulation freeze was somewhat artificial (Beggiato, 2013), Endsley and Kiris (1995) concluded that task performance was not affected by the number and duration of freezes.

6.2.2 Participants

There were 40 participants in the study: 30 males and 10 females, ranging in age from 18 to 79 years, with a mean age of 40.35 years and a standard deviation of 16.26 years. The mean number of years of driving experience was 21.55 with a standard deviation of 16.15 years. Participants were recruited from both Monash University (undergraduate students, post-graduate students and staff) and outside using personal contacts, MUARC participant database and advertising on social media. Participants were required to have either a full driver license or a second-year probationary license. They were also required to drive at least 5,000 km per year. Apart from the aforementioned criteria, participants were not specifically targeted for belonging into any of the demographic categories or for having specific attitudes towards automated driving. They were offered $20 for their participation. Ethics approval was obtained from the Monash University Human Research Ethics Committee.

6.2.3 Apparatus

The MUARC Automation simulator consisted of a car seat and standard controls mounted on a rigid frame (**Figure 6.1**). The simulated vehicle was equipped with an automatic transmission. Visuals were presented on three 46” high brightness bezel-less displays. Each display had a resolution of 1080p and the image refresh rate was 60Hz. The driver and the passenger both had 140° of the horizontal field of view and 45° vertical field of view. The sound was presented via left, right and centre satellite speakers and a subwoofer for LFE (low-frequency effects).

Figure 6.1 *Automation driving simulator for Study 3*

A 10” tablet was used to administer questionnaires. The tablet was mounted on the right side of the simulator dashboard for easy access.

6.2.4 Experimental scenarios

As discussed in Chapter 3, a conservative driving style was adopted for the presentation of automated drives. This was done to minimise the potential for adverse reaction to automated driving. In other words, automated driving was presented as neutral as possible, as of assumed “perfect” average driver. In summary, it is virtually impossible to create a universal automated driving style that will accommodate all driver preferences. Therefore, the experimental scenario itself needed to minimise opportunities for conflicts between the participant’s preferred driving style and the automated driving style, for example, avoiding sharp bends or overtaking situations.

Four scenarios were developed for the study. Scenario 1 and Scenario 2 were created in an urban environment with a 50 km/h speed limit. The road had two lanes and three intersections. Scenario 3 and Scenario 4 were created on a highway in a country environment with a speed limit of 90 km/h. This speed limit was chosen as the highest speed limit allowed on highways in Victoria. Each drive lasted approximately seven minutes. Along each of these drives, participants were exposed to 5 distinctive events. The events were Free (free driving), GW (give way), RF (rain and fog), OC (oncoming car) and VF (vehicle following). A schematic showing an order of events on 50 km/h road is shown in **Figure 6.2** and the order of events on 90 km road in **Figure 6.3**.

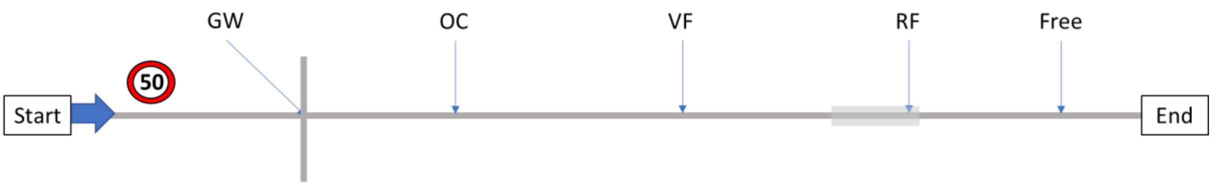


Figure 6.2 *Events in 50 km/h drives*

Figure 6.3 *Events in 90 km/h drives*

Each event contained a question point. At pre-determined locations within each event, the simulation would freeze for 10 seconds manifesting as a sudden stop in travel, absence of car engine sound and still speedometer. **Figure 6.4** illustrates the frozen simulator drive during the RF (rain and fog) event. During each simulation freeze, participants were required to enter their ratings for WTE or WTRC and POS. After 10 seconds the simulation would continue until the following event until all five events had been presented and ratings entered.

Figure 6.4 *An example of a question point (RF event)*

Two of the drives were presented in manual driving mode (Scenario 1 and Scenario 3) and two in automated driving mode (Scenario 2 and Scenario 4). During manual drives, participants were required to control car speed and steering. In automated mode, participants were free of the physical component of the driving task. All experimental scenarios with associated conditions and order of events are presented in **Table 6.3**. Scenarios were presented in a controlled counterbalanced order. Every participant completed four drives during the experimental session.

Table 6.3 *Study 3 experimental scenarios*

Scenario	Speed limit	Control mode	Event 1	Event 2	Event 3	Event 4	Event 5
1	50 km/h	Manual	GW	OC	VF	RF	Free
2	50 km/h	Automated	GW	OC	VF	RF	Free
3	90 km/h	Manual	RF	Free	VF	OC	GW
4	90 km/h	Automated	RF	Free	VF	OC	GW

Free driving event

The Free (free driving) event consisted of driving on a mainly straight road with no other vehicles present in the scene. The question point occurred at the same location for all participants

Give way event

The GW (give way) event from 50 km/h drives is illustrated in **Figure 6.5**. The driver (red car marked with D) approached an intersection with a give way sign. Three vehicles on the main road were crossing the intersection. Vehicle 1 was triggered early to enter the intersection before the driver. Vehicle 2 followed Vehicle 1. The time gap between Vehicle 1 and Vehicle 2 was short, preventing the driver from entering the intersection. Only the second time gap (between Vehicle 2 and vehicle 3) allowed enough time for entering the intersection only if the decision to do so was made quickly. There were no more crossing cars after Vehicle 3 and the driver was able to enter the intersection without any obstructions. The decision point occurred at 5 meters before the stop line.

The second version of the GW event implemented on 90km/h drives involved a roundabout instead of an intersection. However, the event contained the same number of vehicles that formed the same time gaps between them as at the intersection. The roundabout-based GW event is illustrated in **Figure 6.6**. The question point occurred just before the stop line.

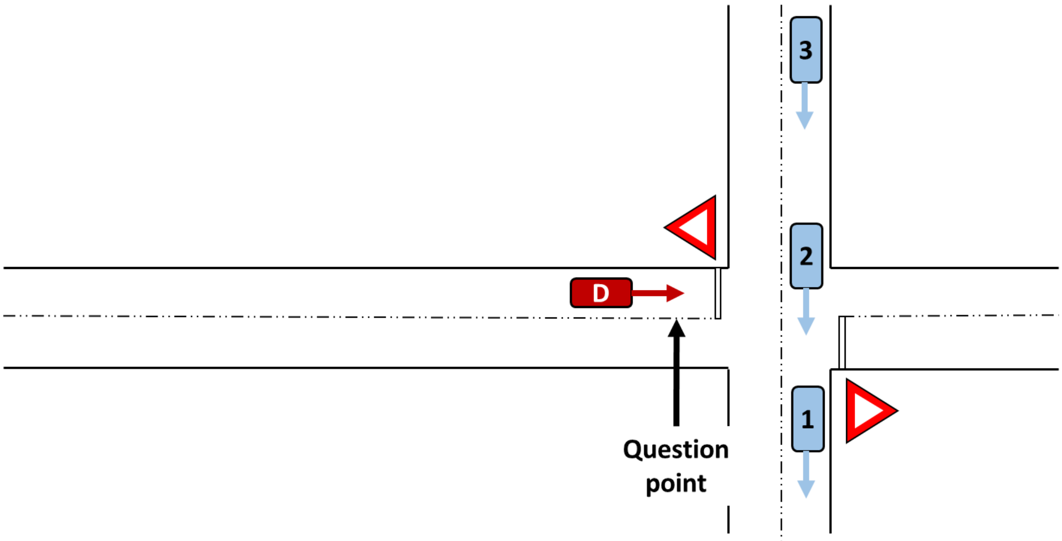


Figure 6.5 *GW event in 50 km/h drive*

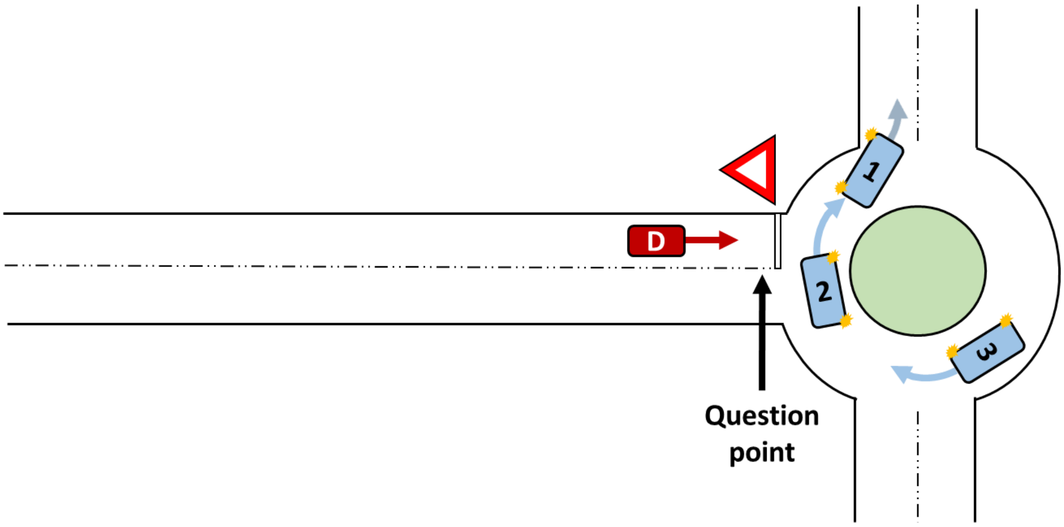


Figure 6.6 *GW event in 90 km/h drive*

Oncoming car event

The OC (oncoming car) event is illustrated in **Figure 6.7**. The driver (D) was on a straight road and encountered two approaching vehicles ahead. The front vehicle was a truck (T). Behind the truck, a car (FC) was following at close distance with right indicators turned on, signalling possible intention to overtake the truck. The FC was also driving close to the centreline. The question point occurred when the distance between the driver (D) and the T was 30 meters. After the simulation continued, the FC stopped indicating right and retreated towards the centre of the lane.

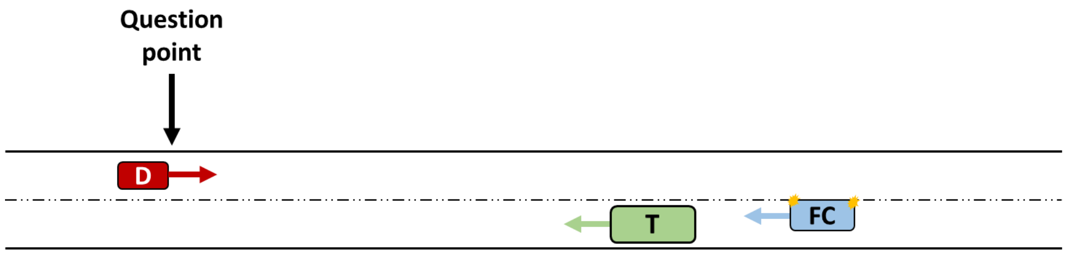


Figure 6.7 *OC event*

Rain and fog event

The RF (rain and fog) event is illustrated in **Figure 6.8**. In this event, the driver entered into the gradually heavier rain and fog conditions. The visibility was set to 300 m in the simulation software. The simulator car wipers activated automatically when the rain started. The maximum intensity of the rain and the maximum density of the fog was reached in approximately three seconds. The question point occurred at approximately 20 seconds of driving in such conditions. After being paused for 10 seconds allocated for entering responses in the questionnaire, the simulation continued and rain and fog quickly cleared up. During automated mode drives the simulator car did not reduce speed in these conditions.

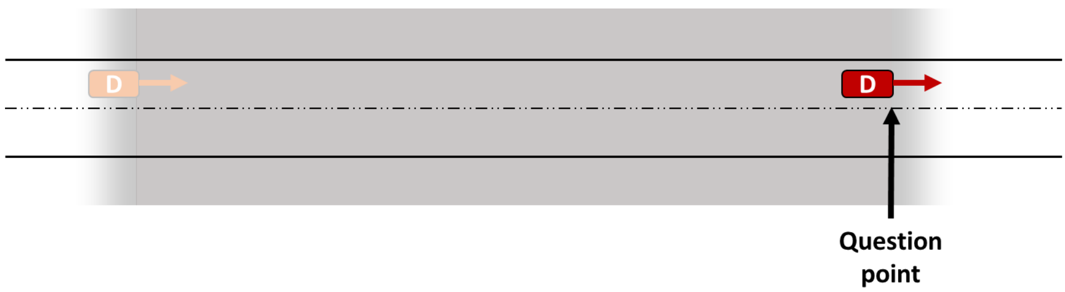


Figure 6.8 *RF event*

Vehicle following event

The VF (vehicle following) event is illustrated in **Figure 6.9**. A lead vehicle (LV) pulled out from the service station well ahead of the driver (D). At first, LV was driving slowly and gently accelerating allowing the driver to reduce the distance between them. When the time headway (TH) between D and LV reached three seconds or less, LV started velocity tracking D. During this phase of velocity tracking, time headway between D and LV was gradually being reduced over approximately 15 seconds. When time headway reached 1.5 seconds, it was maintained by adjusting the speed of LV. After 20 seconds of driving at this time headway, a question point for this event occurred. After the simulation continued, LV gently accelerated to above the speed limit (110 km/h) and gradually disappeared from the view of the driver. If the driver (only when driving in manual control mode) slowed down to under 30 km/h, the question was presented and LV accelerated to above the speed limit and disappeared from the view of the driver.

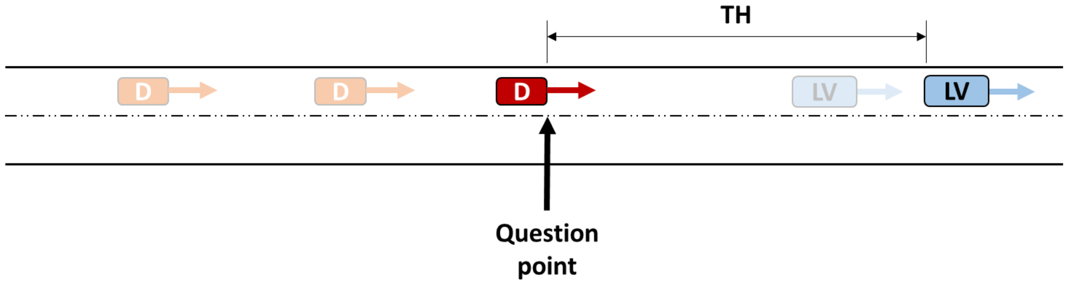


Figure 6.9 *VF event*

6.2.5 Collected data

During each experimental drive, a questionnaire with five questions was administered. Each question had two parts. Part A of the question required the participant to select one of four options to rate WTE (willingness to engage automation) during manual driving (**Figure 6.10a**) or WTRC (willingness to resume manual control) during automated driving (**Figure 6.10b**). The four available categories were Very unwilling, Unwilling, Willing and Very Willing. Part B of the question rated the subjective POS (perception of the safety) of the current situation. The POS score was entered using a sliding scale, ranging from 0 for very unsafe to 100 for very safe. Every participant completed four such questionnaires during each experimental session.

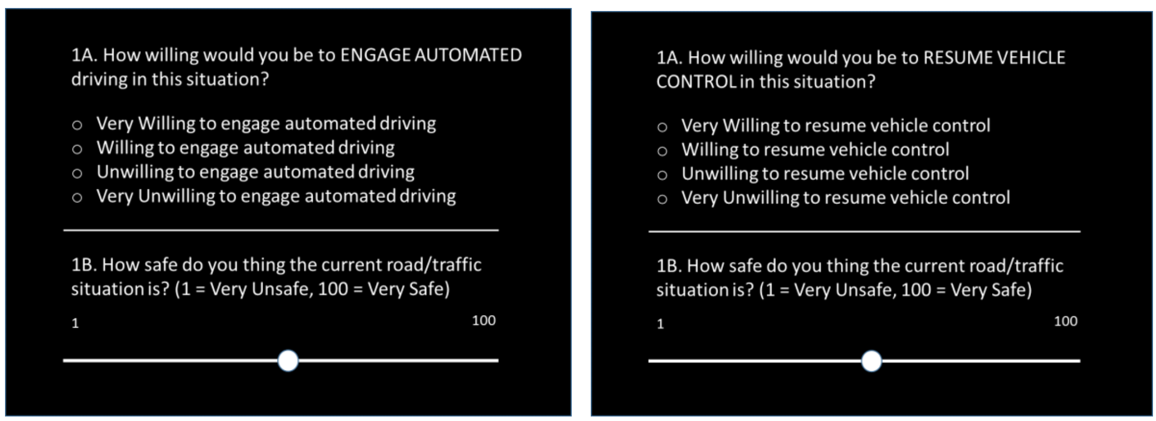


Figure 6.10 *Example of a question* ***a)*** *manual drive (WTE and POS) and* ***b)*** *automated drive (WTRC and POS)*

In addition to questionnaires, simulator data (driver coordinates, speed, lateral position, steering wheel angle, braking, accelerator, and other vehicles' coordinates and speeds) were recorded during manual simulator drives.

6.2.6 Procedure

The experimental session was conducted in the automation driving simulator at Monash University Accident Research Centre. Study 3 procedures are illustrated in **Figure 6.11**.

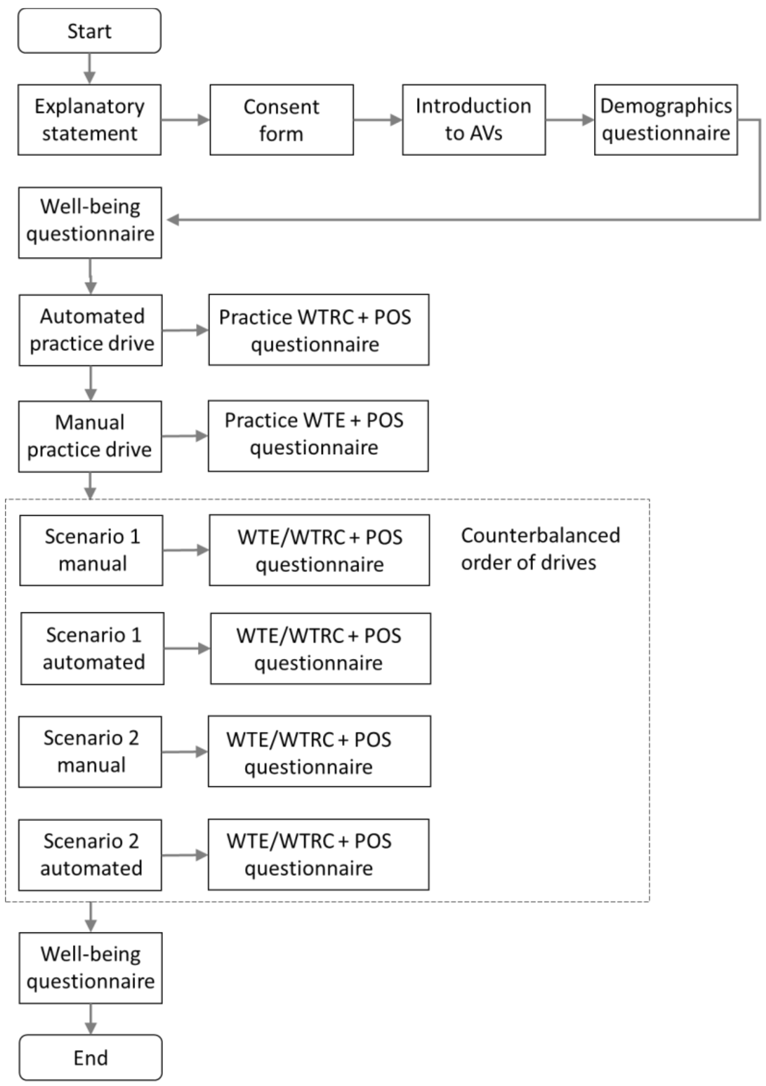


Figure 6.11 *Study 3 procedure*

Upon arrival, participants completed an informed consent form, as approved by the Monash University Ethics Committee, and read the experimental instructions. They were then given a brief introduction to automated vehicles, different levels of vehicle automation with an emphasis on Level 3 automation and choice of control mode since they would be experiencing Level 3 automated driving in the simulator. Participants were then presented with a definition of willingness and an explanation of an experimental task. They were instructed that their task was to answer questionnaires during all simulator drives, manual and automated without the need to change control mode since vehicle automation was capable of safely handling all situation presented in drives. During this introduction, to gain a better understanding of the questionnaire, participants were asked to suggest situations when they would be willing to engage in automated driving and situations when they would be willing to resume control of the vehicle. This was followed by a demographics questionnaire that also included questions about driving habits, subjective driving skills and attitudes toward technologies. Before entering the simulator, a pre-drive Well-being questionnaire was administered. After entering the simulator two practice drives were presented to familiarise participants with the simulator controls, visuals and tablet-based questionnaire. The automated practice drive was presented first followed by a manual practice drive. Both drives were identical and contained three events. At each event, participants were given a practice question point. At the selected location the simulation would stop for 15 seconds giving participants time to practice entering their ratings in the questionnaire. Following practice drives four experimental scenarios were presented in a counterbalanced order. During each drive, participants were instructed to observe road and traffic conditions. At each question point, participants would enter their ratings for WTE (during manual drives) or WTRC (during automated drives) and POS. After the end of the fifth event, each drive was completed. For every manual drive, the simulator replay file was saved. After all four experimental drives were completed participants would return to the control desk where a post-drive Well-being questionnaire was administered. At the end of the session, participants were offered $20 for their participation and encouraged to make comments. The total duration of the experimental session was about 60 minutes.

6.3 Results

6.3.1 Willingness to engage automated control and willingness to resume manual control

The effects of experimental conditions on WTE/WTRC (hypotheses H6.1 and H6.2) were analysed using the GEE method. The unstructured working correlated matrix was selected. For modelling the dependent variable, the ordinal logit model and cumulative logit link function were selected. The independent variables were speed (50 km/h and 90km/h), and situation complexity (Low complexity and High complexity). As experimental questions were different in manual and automated drives, two full factorial models, one for WTE and another for WTRC, were specified to allow examination of all possible main and interaction effects. All non-significant effects were removed from the model one at the time until only those effects that were significant at p <= .05 remained in the model. For each model, a table containing the parameter estimates (B coefficients) for the significant main effect of the level of complexity is provided. For each parameter, also provided is the standard error of B, the confidence intervals of the Wald chi-square, the Wald chi-square value, whether the parameter attained significance, the exponential value of B (that is, the relative odds ratio), and the 95% confidence intervals for the relative odds ratio.

WTE model

The final GEE model for WTE, observed during manual drives, was made up only of a significant main effect of the level of complexity ($\chi^2(4) = 34.50$, $p < .001$). There was no statistically significant effect of speed on WTE. The parameter estimates (B coefficients) for the significant main effect of level of complexity are provided in **Table 6.4**.

Table 6.4 *WTE model parameter estimates*

Parameter	Hypothesis Test			Exp(B)	95% Wald CI for Exp(B)	
	Wald χ^2	df	Sig.		Lower	Upper
Event						
VF	9.507	1	0.002	0.439	0.260	0.741
RF	18.495	1	0.000	0.246	0.130	0.467
OC	27.390	1	0.000	0.147	0.072	0.301
GW	10.224	1	0.001	0.285	0.132	0.615
Free	.	.	.	1	.	.

These tests compared WTE ratings at the low complexity event (Free) with WTE ratings at high-complexity events and WTE ratings at two different speeds. The results confirmed that WTE at the low-complexity event was statistically significantly different from POS at high-complexity events. The examination of **Table 6.4** revealed that WTE for each high complexity event was significantly reduced when compared with the Free event. Therefore, participants were significantly less willing to engage in automated driving during high-complexity events. The comparison of mean WTE scores is illustrated in **Figure 6.12**. To enable calculation of means, each WTRC category was assigned a value as follows: 1 for very unwilling, 2 for unwilling, 3 for willing and 4 for very willing.

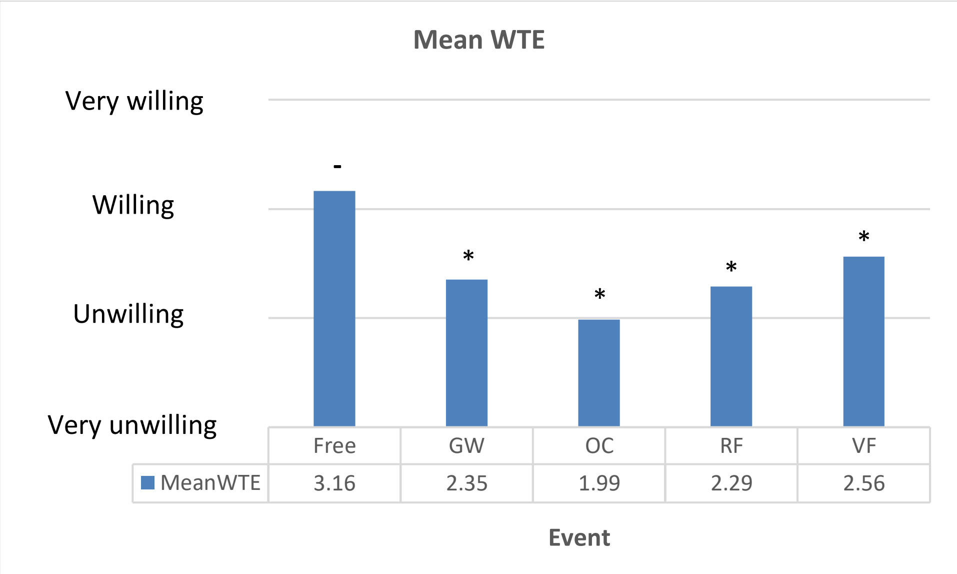


Figure 6.12 *Mean WTE scores (* p<0.05)*

WTRC model

The final GEE model for WTRC, observed during automated driving, was made up of a significant main effect of the level of complexity ($\chi^2(4) = 58.36$, $p < .001$) and a significant main effect of speed ($\chi^2(1) = 5.16$, $p = .023$). The WTRC model parameter estimates (B coefficients) for the significant main effects are provided in **Table 6.5**.

Table 6.5 *WTRC model parameter estimates for SC and Speed*

Param.	Hypothesis Test			Exp(B)	95% Wald CI for Exp(B)	
	Wald χ^2	df	Sig.		Lower	Upper
Event						
VF	14.162	1	0.000	2.090	1.424	3.067
RF	34.271	1	0.000	6.227	3.376	11.486
OC	43.271	1	0.000	9.357	4.806	18.216
GW	32.164	1	0.000	5.106	2.907	8.970
Free	.	.	.	1	.	.
Speed						
90km/h	5.162	1	.023	1.376	1.045	1.811
50km/h	.	.	.	1	.	.

The examination of **Table 6.5** revealed that WTRC for each high complexity event was significantly increased when compared with the Free event. Parameter estimates confirmed that WTRC at the low-complexity event was statistically significantly different from WTRC at every high-complexity event and significantly different between two driving speed categories. In summary, participants were significantly more willing to resume manual control of the vehicle during high-complexity events and at a higher speed.

The comparison of mean WTRC scores is illustrated in **Figure 6.13**.

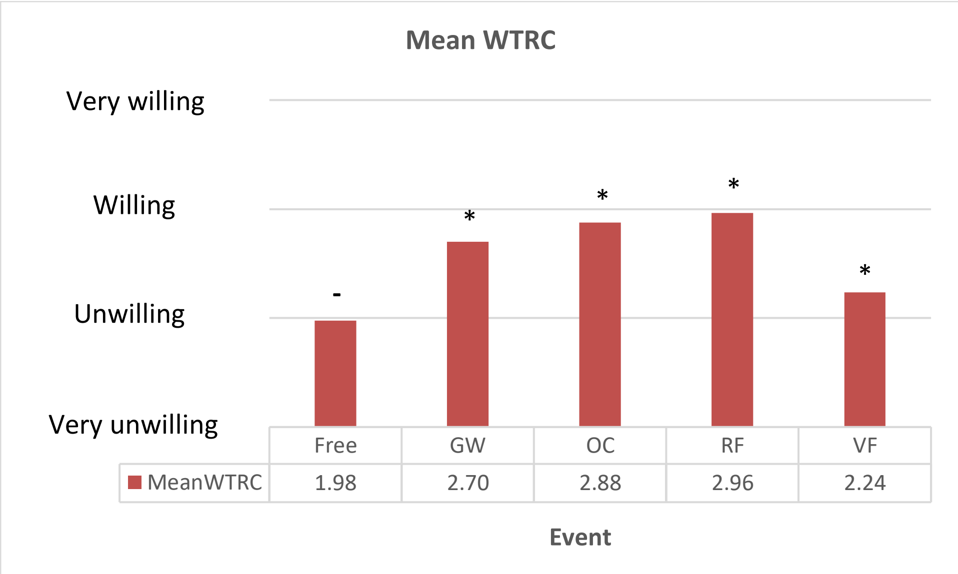


Figure 6.13 *Mean WTRC scores (* p<0.05)*

6.3.2 Perception of safety

The effects of experimental conditions on POS (hypotheses H6.3, H6.4 and H6.5) were analysed using the GEE (generalising estimating equations) method. The unstructured working correlated matrix was selected. For modelling the dependent variable, the linear model and identity link function was selected. The independent variables were speed (50 km/h and 90km/h), driving mode (Manual and Automated) and situation complexity (Low complexity and High complexity events). A full factorial model was specified to allow examination of all possible main and interaction effects, and non-significant effects were removed from the model one at the time until only those effects that were significant at p <= .05 remained in the model. The final GEE model was made up of four significant effects: the main effect of situation complexity ($\chi^2(4) = 175.07$, $p < .001$), whereby POS for the low-complexity event was statistically significantly higher than POS for the high-complexity events, the main effect of driving mode ($\chi^2(1) = 5.15$, $p = .023$, and two significant interaction effects. The first interaction was between speed and situation complexity ($\chi^2(5) = 14.07$, $p = .015$) and the second interaction was between driving mode and situation complexity ($\chi^2(4) = 12.37$, $p < .015$).

The parameter estimates (B coefficients) for the significant main effect of levels of complexity and two statistically significant interactions are provided in **Table 6.6**. For each parameter, also provided is the B coefficient, the standard error of B, the 95% confidence intervals for the coefficients, the Wald chi-square value and whether the parameter attained significance.

Table 6.6 *POS model parameter estimates*

Parameter	B	SE	95% Wald CI		Hypothesis Test		
			Lower	Upper	Wald χ^2	df	Sig.
Event							
VF	-13.846	2.420	-18.590	-9.102	32.722	1	.000
RF	-40.279	2.999	-46.158	-34.399	180.277	1	.000
OC	-32.255	3.287	-38.699	-25.811	96.242	1	.000
GW	-19.922	3.179	-26.155	-13.690	39.249	1	.000
Free	0	.	.	.	.	.	.
Driving mode							
Automated	2.885	1.247	.440	5.331	5.347	1	.021
Manual	0	.	.	.	.	.	.
Speed*Event							
90 km/h * VF	2.089	2.460	-2.733	6.911	.721	1	.396
50 km/h * VF	0	.	.	.	.	.	.
90 km/h * RF	-3.464	2.273	-7.920	.992	2.322	1	.128
50 km/h * RF	0	.	.	.	.	.	.
90 km/h * OC	-4.059	2.110	-8.195	.076	3.701	1	.054
50 km/h * OC	0	.	.	.	.	.	.
90 km/h * GW	1.784	2.359	-2.841	6.410	.572	1	.450
50 km/h * GW	0	.	.	.	.	.	.
90 km/h * Free	-5.487	2.728	-10.835	-.139	4.043	1	.044
50 km/h * Free	0	.	.	.	.	.	.
Driving mode*Event							
Automated * VF	10.749	3.453	3.981	17.517	9.689	1	.002
Manual * VF	0	.	.	.	.	.	.
Automated * RF	1.727	3.163	-4.474	7.927	.298	1	.585
Manual * RF	0	.	.	.	.	.	.
Automated * OC	2.359	3.087	-3.692	8.409	.584	1	.445
Manual * OC	0	.	.	.	.	.	.
Automated * GW	6.187	3.292	-.266	12.641	3.532	1	.060
Manual * GW	0	.	.	.	.	.	.
Automated * Free	0	.	.	.	.	.	.
Manual * Free	0	.	.	.	.	.	.

The main effect of SC on POS

The examination of parameter estimates of the effect of SC (situation complexity) on POS revealed that there was a statistically significant difference in POS ratings between the low-complexity event and each of the high complexity events. Estimated marginal means of POS for each event, sorted in descending order are illustrated in **Figure 6.14**. POS score for the Free event was the highest, while the score of POS for the RF (rain and fog) event was the lowest. The model predicted a difference of 40 rating points between the POS score at the Free event and the POS score at the RF event.

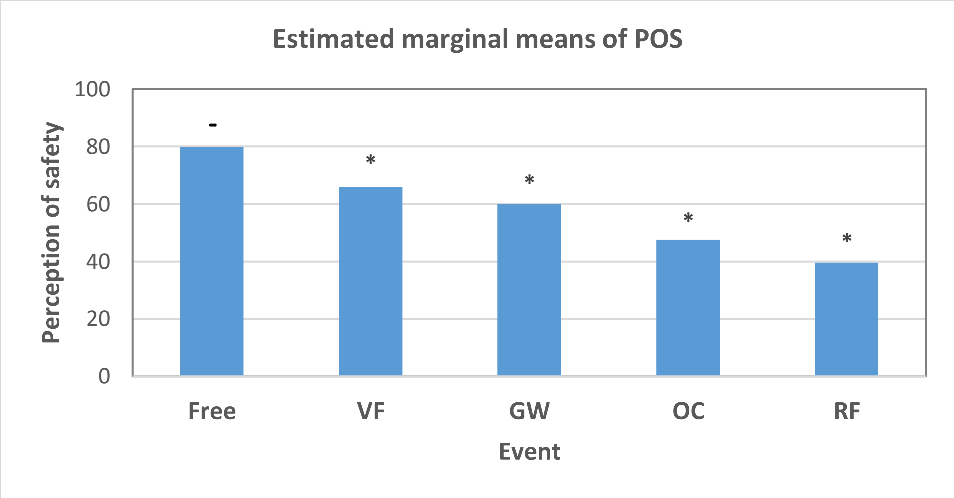


Figure 6.14 *Estimated marginal means of POS for each event (* p <0.05)*

The main effect of driving mode on the perception of safety

The test compared POS at Manual drives with POS at Automated drives. The model suggested that predicted POS during automated driving was higher by 2.885 rating points compared to POS during manual driving. Although statistically significant the difference between observed POS was not large.

Interaction effect of speed and situation complexity

Examination of parameter estimates (B coefficients) for the significant interaction effect of speed*event revealed that the statistically significant interaction of speed and SC (situation complexity) was observed only for the Free event and a marginally significant interaction for the OC (oncoming car) event. Estimated marginal means of POS for each event are illustrated in **Figure 6.15.**

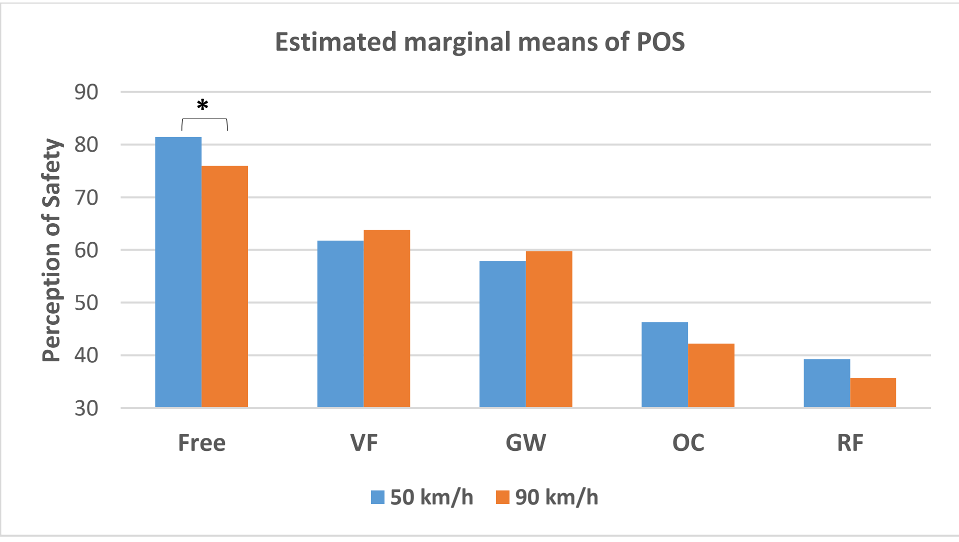


Figure 6.15 *Estimated marginal means of POS for the interaction of events (SC) and speed (* p < 0.05)*

Interaction effect of driving mode and situation complexity

Examination of parameter estimates for this interaction of driving mode and SC revealed a significant effect of driving mode on POS for the VF (vehicle following) event and a marginally significant effect of driving mode for the GW (give way) event**.** Estimated marginal means of POS for each event are illustrated in

Figure 6.16. For both the VF event and the GW event, the estimated POS was higher in automated driving mode.

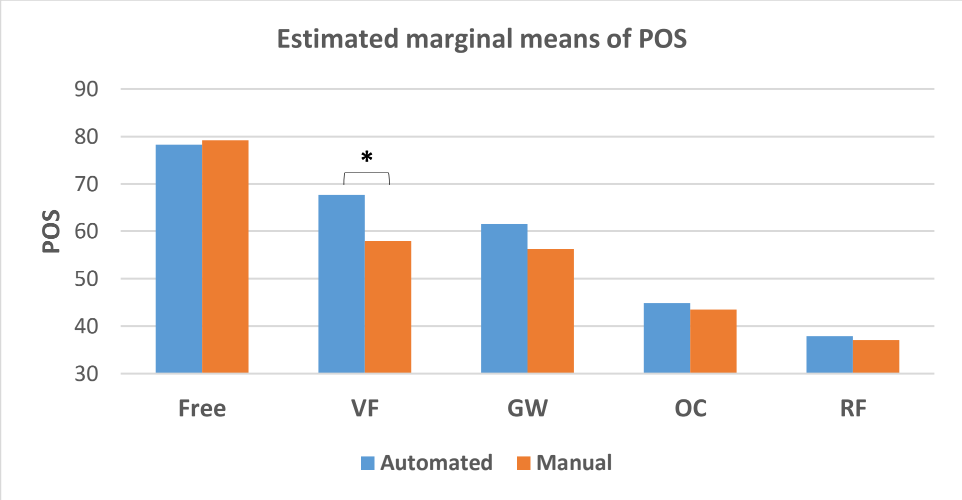


Figure 6.16 *Estimated marginal means of POS for the interaction of events (SC) and driving mode (* p < 0.05)*

6.3.3 Preference of vehicle control mode

The preferred vehicle control mode is a variable derived from WTE and WTRC ratings. It allowed two separate datasets to be combined and therefore, investigation of the effect of driving mode across both driving conditions (H6.6). The new dependent variable (Preference) was calculated according to the rules presented in **Table 6.7**. The logic behind these rules was that, if the driver in a current driving mode was very unwilling to change the driving mode then a strong preference for the current driving mode was assigned to the new variable. And vice versa, if the driver was very willing to change the driving mode a strong preference for the alternate driving mode was assigned to the new variable.

Table 6.7 *Rules for calculating preference of vehicle control mode*

Level of WTE/WTRC	Driving mode	Preference of vehicle control mode
Very unwilling (WTRC)	Automated	2 (Strong automated)
Unwilling (WTRC)	Automated	1 (Automated)
Willing (WTRC)	Automated	-1 (Manual)
Very willing (WTRC)	Automated	-2 (Strong manual)
Very unwilling (WTE)	Manual	-2 (Strong manual)
Unwilling (WTE)	Manual	-1 (Manual)
Willing (WTE)	Manual	1 (Automated)
Very willing (WTE)	Manual	2 (Strong automated)

The overview of proportions of driving mode preferences for all categories and events are illustrated in **Figure 6.17**. Each preference level was colour-coded, and counts presented as percentages of the total number of selections for each category.

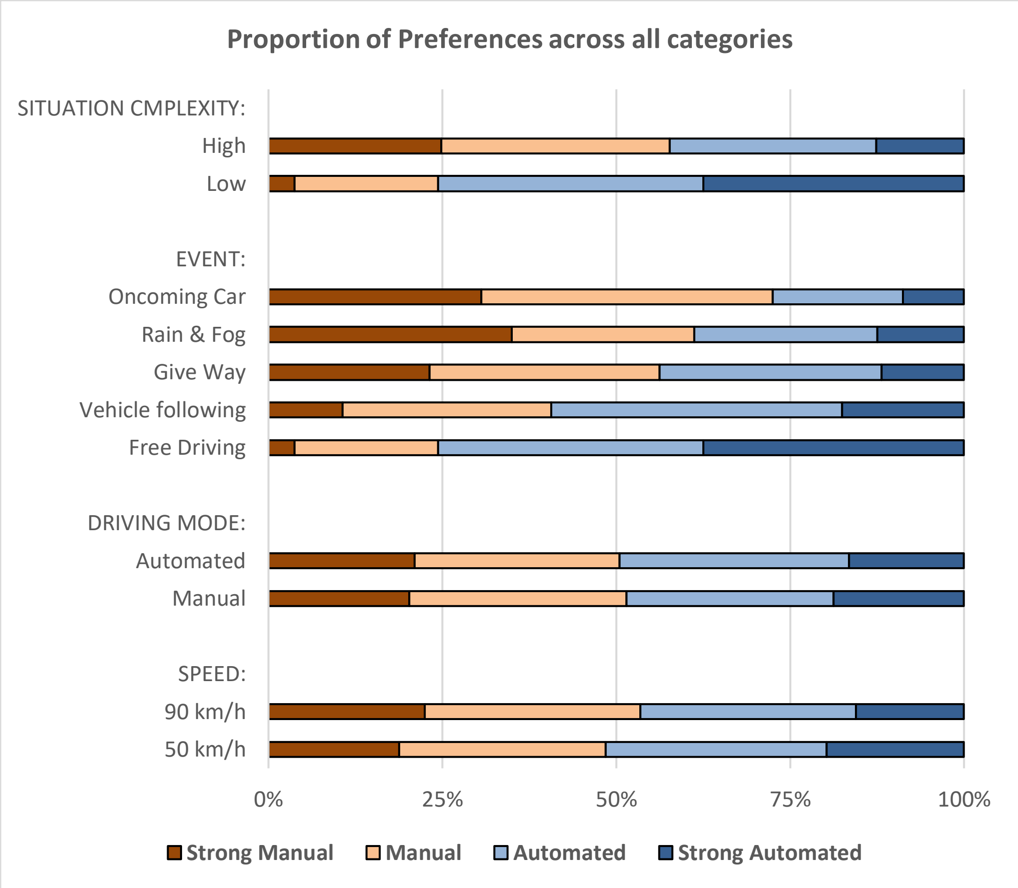


Figure 6.17 *Distribution of preferred vehicle control mode preference for each event*

The effects of experimental conditions on the Preference of vehicle control mode (hypothesis H6.6) were analysed using the GEE method. The unstructured working correlated matrix was selected. For modelling the dependent variable, the ordinal logit model and cumulative logit link function were selected. The independent variables were driving mode (Manual and Automated), speed (50 km/h and 90km/h), and SC (Low complexity and High complexity). A full factorial model was specified to allow examination of all possible main and interaction effects, and non-significant effects were removed from the model until only significant effects ($p \leq .05$) remained in the model. The final GEE model for Preference of the driving mode was made of a significant main effect for the level of complexity ($\chi^2(4) = 128.46$, $p < .001$), speed ($\chi^2(1) = 6.47$, $p = .011$) and the interaction effect between driving mode and level of complexity ($\chi^2(5) = 81.10$, $p < .001$).

The parameter estimates (B coefficients) for both significant main effects and the interaction effect are provided in **Table 6.8**. For each parameter, also provided is the standard error of B, the Wald chi-square value, whether the parameter attained significance, the exponential value of B (that is, the relative odds ratio), and the 95% confidence intervals for the relative odds ratio.

Examination of parameter estimates revealed that the driving speed had a small effect on the preferred driving mode, with the odds favouring manual driving mode at a higher speed. The odds of the preference of automated driving mode increased significantly with a higher level of situation complexity.

Table 6.8 *Parameter estimates for the Preference of the driving mode*

Parameter	Hypothesis Test			Exp(B)	95% Wald CI for Exp(B)	
	Wald χ2	df	Sig.		Lower	Upper
Speed						
90 km/h	6.473	1	.011	.820	.703	.955
50 km/h	.	.	.	1	.	.
Event						
VF	10.184	1	.001	.507	.334	.770
RF	35.187	1	.000	.247	.155	.392
OC	109.046	1	.000	.125	.084	.184
GW	35.248	1	.000	.245	.154	.390
Free	.	.	.	1	.	.
Event*Mode						
VF*Auto	.085	1	.770	1.067	.690	1.649
VF*Man	.	.	.	1	.	.
RF*Auto	31.207	1	.000	.530	.424	.662
RF*Man	.	.	.	1	.	.
OC*Auto	22.615	1	.000	2.213	1.595	3.069
OC*Man	.	.	.	1	.	.
GW*Auto	.545	1	.460	1.129	.818	1.558
GW*Man	.	.	.	1	.	.
Free*Auto	2.139	1	.144	.764	.533	1.096
Free*Man	.	.	.	1	.	.

Parameter estimates for interaction between events and driving mode (event*driving mode) explained the absence of the main effect of driving mode on the preference. Only two interactions of driving mode with events were statistically significant, one with RF (rain and fog) event and the second with OC (oncoming car) event. Comparison of Beta coefficients revealed a crossover interaction which resulted in no overall effect of driving mode on preference. Encountering RF event in automated driving mode significantly increased odds of preference for manual control mode, when compared with experiencing RF event during manual driving. Encountering OC event in automated driving mode had the opposite effect. When compared with manual driving, the odds of preference for automated control mode were significantly reduced. In summary, these results confirm the significant effect of complexity, speed and interaction effects of driving mode with two events (RF and OC) on POS.

6.3.4 Association of POS and WTE/WTRC

The aim of hypothesis H6.7 was to explore the association between POS and related WTE/WTRC. Since willingness was a categorical variable with four categories, Pearson/Spearman correlation was not suitable as a statistical test of this hypothesis. Instead, the correlation between POS and WTE/WTRC was tested with two GEE models, one for the dataset originating from automated drives and the second dataset from manual drives. In these models, POS outcomes were tested by willingness categories being used as predictors. For each model, the exchangeable working correlated matrix was selected. For modelling the dependent variable (POS), the linear model and identity link function were selected. The independent variables were WTE or WTRC. A main-effect only model was specified for each dataset.

Effect of WTE on POS during manual driving

There was a significant main effect of WTE ($\chi^2(3) = 171.30$, $p < .001$) on POS (Perception of Safety). The model parameter estimates are summarised in **Table 6.9** indicating significant differences in estimated POS for each level of WTE. Beta coefficients indicate that increase in the level of WTE is associated with increased POS

Table 6.9 Parameter Estimates of WTE for POS (Manual driving)

Parameter	B	Std. Error	95% Wald CI		Hypothesis Test		
			Lower	Upper	Wald χ^2	df	Sig.
WTE							
Very willing	40.655	3.6361	33.529	47.782	125.015	1	.000
Willing	37.656	3.2938	31.201	44.112	130.701	1	.000
Unwilling	19.774	3.2534	13.398	26.151	36.943	1	.000
Very unwilling	0	.	.	.	.	.	.

Effect of WTRC on POS during automated driving

There was a significant main effect of WTRC ($\chi^2(3) = 166.21$, $p < .001$) on POS. The parameter estimates are summarised in **Table 6.10** indicating significant differences in estimated POS for each level of WTRC. Beta coefficients indicate that increase in the level of WTRC is associated with a reduction in POS.

Table 6.10 *Parameter Estimates of WTRC for POS (Automated driving)*

Parameter	B	Std. Error	95% Wald CI		Hypothesis Test		
			Lower	Upper	Wald χ^2	df	Sig.
WTRC							
Very willing	-42.971	3.7217	-50.265	-35.677	133.314	1	.000
Willing	-19.647	3.5343	-26.574	-12.720	30.901	1	.000
Unwilling	-8.300	3.3700	-14.905	-1.695	6.066	1	.014
Very unwilling	0	.	.	.	.	.	.

In summary, these results confirmed a strong association between WTE/WTRC and POS. An increase in the level of WTE was associated with increased POS while an increase in the level of WTRC was associated with a reduction in POS. Combined plots of estimated marginal means of POS for levels of WTE and WTRC are presented in **Figure 6.18**.

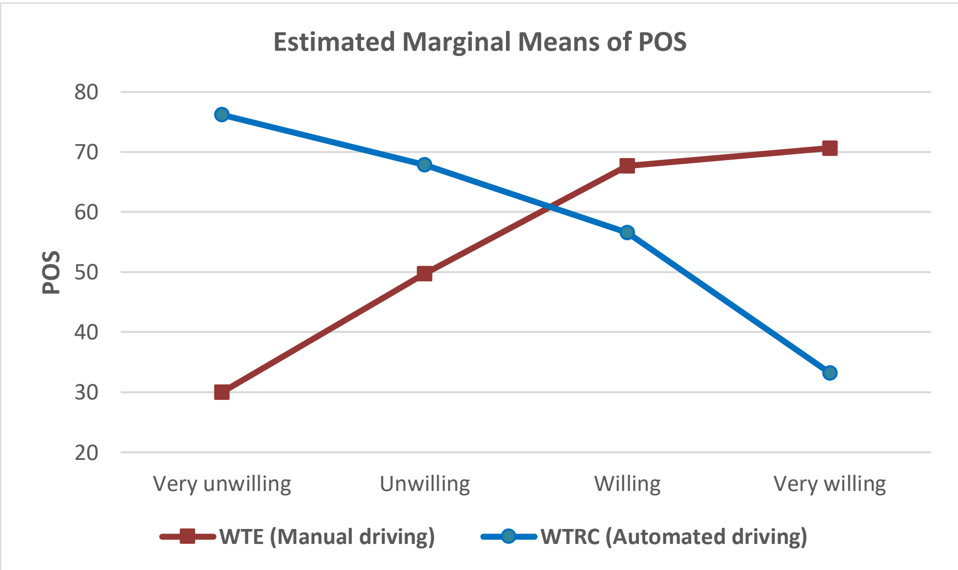


Figure 6.18 *Summary of Estimated marginal means of POS for levels of willingness*

6.3.5 Effect of demographics categories and attitudes on WTE/WTRC

Results below report the findings of the effects of demographics categories and attitudes on WTE (recorded during manual drives) and WTRC (recorded during automated drives). Multiple linear regression models were calculated to predict WTE/WTRC based on driver characteristics. For the analysis, all attitude variables (scored on a five-point Linkert scale) were treated as continuous variables and WTE/WTRC ratings were averaged for each participant (across all speeds, driving modes and events). All driver characteristics variables used in a multiple regression model are summarised in **Table 6.11**.

Table 6.11 *Driver characteristics variables*

Category	Values
Gender	0 = Female, 1 = Male
Age	Number of years
Driving experience	Number of years
Transmission of the participant's vehicle	0 = Automatic, 1 = Manual
Advanced assistance systems (ACC, LKS …) present in the participant's vehicle	0 = No, 1 = Yes
Kilometres per week	Number of km
Driving environment	0 = Urban, 1 = Rural
Traffic conditions	0 = Light/Medium, 1 = High
Previous accidents	0 = No, 1 = Yes
Driving confidence (How confident are you in your general driving skills?)	1 = Not confident 2 = Somewhat confident 3 = Moderately confident 4 = Confident 5 = Very confident
Safe driver (How safe a driver do you consider yourself to be?)	1 = Very unsafe 2 = Unsafe 3 = Neutral 4 = Safe 5 = Very Safe
Driving enjoyment (How enjoyable is driving a car for you?)	1 = Not enjoyable 2 = Somewhat enjoyable 3 = Moderately enjoyable 4 = Mostly enjoyable 5 = Very enjoyable
Attitude towards technology (What is your attitude towards new technologies/gadgets in vehicles?)	1 = Very negative 2 = Negative 3 = Neutral 4 = Positive 5 = Very positive
Trust in automation (Would you trust an automated system (similar to the autopilot on an aeroplane) to control the car for you, if your car was equipped with such a system?)	1 = No trust at all 2 = Low trust 3 = Moderate trust 4 = High trust 5 = Complete trust
Technology adoption (How would you rate yourself as an adopter of new technologies?)	1 = Very early adopter 2 = Early adopter 3 = Average adopter 4 = Late adopter 5 = Very late adopter

For statistical modelling, WTE/WTRC ratings were assigned a numerical value (1 = Very unwilling, 2 = Unwilling, 3 = Willing, 4 = Very willing) and averaged for each participant (across two speed and five event categories). Therefore, the resultant WTE/WTRC rating for every participant was an average of 10 scores for WTE and 10 scores for WTRC. A descriptive analysis, correlations and scatter plots vs POS were conducted before the exploration of the model. The minimal models are presented below (the simplest regression model with high R^2 and normally distributed residuals).

WTE model (manual drives)

A significant regression equation was found ($F(3, 36) = 14.022$, $p < .001$) with an R^2 of .539 and adjusted R^2 of .500. The model coefficients are summarised in **Table 6.12**.

***Table 6.12** Coefficients of the minimum linear model for WTE*

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95% CI for B	
	B	SE	Beta			Lower	Upper
(Constant)	2.587	.395		6.554	.000	1.787	3.388
Kms/week	.002	.000	.488	4.244	.000	.001	.003
Enjoy	-.332	.073	-.519	-4.515	.000	-.480	-.183
Trust	.237	.079	.338	2.988	.005	.076	.398

The WTE score increased .002 for every kilometre driven per week, decreased .332 for every increase in the level of driving enjoyment and increased .237 for every increase in the level of trust in automation. Number of kilometres driven per week (B = .002, t = 4.244, p < .001), driving enjoyment (B = -.332, t = -4.515, p < .001) and trust in automation (B = .237, t = 2.988, p = .005) were significant predictors of POS. For example, the predicted WTE score for a participant who drives 200 km per week, rated driving enjoyment at 4 (Mostly enjoyable) and trust in automation at 2 (Low trust) would be 2.133. This score suggests that the participant would be unwilling to engage in automated driving. The introduction of quadratic variables did not improve the model.

WTRC model (automated drives)

A significant regression equation was found ($F(3, 36) = 7.001$, $p = .001$) with an R^2 of .368 and adjusted R^2 of .316. The model coefficients are summarised in **Table 6.13**.

***Table 6.13** Coefficients of the minimum linear model for WTRC*

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95% CI for B	
	B	SE	Beta			Lower	Upper
(Constant)	2.438	.434		5.612	.000	1.557	3.319
Transmission	.500	.218	.307	2.300	.027	.059	.942
Enjoy	.229	.080	.379	2.858	.007	.067	.392
Trust	-.268	.088	-.403	-3.026	.005	-.447	-.088

The model coefficients indicated that the average WTRC score increased .500 for the driver of a car with a manual transmission, increased .229 for every increase in the level of driving enjoyment and decreased .268 for every increase in the level of trust in automation. Being a driver of a car with manual transmission ($B = .500$, $t = 2.300$, $p = .027$), driving enjoyment ($B = .229$, $t = 2.858$, $p = .007$) and trust in automation ($B = -.268$, $t = -3.026$, $p = .005$) were significant predictors of average WTRC. For example, the predicted WTRC score for a participant who drives a car with automatic transmission, rated driving enjoyment at 4 (Mostly enjoyable) and trust in automation at 2 (Low trust) would be 2.818. This score suggests that the participant would be willing to resume manual control of the vehicle.

Scatterplots of trust in automation vs WTRC and driving enjoyment vs WTRC suggested a possible non-linear relationship between these variables and POS. Therefore, new variables representing a square value of trust in automation and the square value of driving enjoyment were calculated and added to the model. The new minimal model consisted of transmission, squared driving enjoyment level and squared trust in automation level. A significant regression equation was found ($F(3, 36) = 7.242$, $p = .001$) with an R^2 of .376 and adjusted R^2 of .324. The model coefficients are summarised in **Table 6.14**.

Table 6.14 *Coefficients of the minimum non-linear model for WTRC*

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95% CI for B	
	B	SE	Beta			Lower	Upper
(Constant)	2.424	.244		9.928	.000	1.929	2.919
Transmission	.516	.217	.316	2.381	.023	.076	.956
Trust SQ	-.041	.013	-.412	-3.105	.004	-.068	-.014
Enjoy SQ	.031	.011	.378	2.864	.007	.009	.053

Car transmission ($B = .516$, $t = 2.381$, $p = .023$), square of driving enjoyment ($B = .031$, $t = 2.864$, $p = .007$) and square of trust in automation ($B = -.041$, $t = -3.105$, $p = .004$) were significant predictors of average WTRC. The addition of the non-linear variables did not significantly improve the existing model however, this was the best model as no other variable could improve it.

6.3.6 Summary of results

A summary of all results, including hypotheses and statistical methods used, is presented in **Table 6.15**.

Table 6.15 *Summary of Study 3 results*

H#	Hypothesis	Statistical methods	Results
H6.1	Increase in SC has a negative effect on the WTE and a positive effect on WTRC	GEE WTE model GEE WTRC model	Confirmed for both WTE and WTRC
H6.2	The higher driving speed has a negative effect on WTE and a positive effect on WTRC		Confirmed for WTRC No effect of speed on WTE
H6.3	Increase in SC has a negative effect on the POS	GEE POS model	Confirmed
H6.4	The automated driving mode has a positive effect on the POS		Confirmed Confirmed for interaction with VF
H6.5	Increase in driving speed has a negative effect on POS		Confirmed for interaction with Free driving event
H6.6	The engaged driving mode has an effect on the preference of driving mode.	GEE model for Preference of driving mode	Confirmed for interactions with RF and OC events
H6.7	Higher POS is negatively associated with WTE and positively associated with WTRC	GEE WTE model GEE WTRC model	Confirmed for both WTE and WTRC
H6.8	Driver characteristics and attitudes can be used as predictors of overall WTE and WTRC	Multiple regression WTE model	Confirmed, significant WTE predictors were kilometres travelled per week, driving enjoyment and trust in automation
		Multiple regression WTRC model	Confirmed, significant WTRC predictors were car transmission, driving enjoyment and trust in automation

6.4 Discussion

The majority of hypotheses concerning the effects of external factors on WTE/WTRC such as the negative effect of SC (situation complexity) on WTE and positive effect of SC on WTRC, and strong association between WTE/WTRC and POS, the negative effect of driving enjoyment on WTE and positive effect of trust in automation on WTE, were supported. The exploration of the effects of driver characteristics identified a positive effect of the number of kilometres travelled per week on WTE and the positive effect of manual vehicle transmission on WTRC. Two of the attitude variables had a statistically significant effect on dependent variables: trust in automation and driving enjoyment.

6.4.1 Willingness to engage automated control and willingness to resume manual control

Effect of situation complexity

The level of SC (situation complexity) had a significant effect on both WTE and WTRC. The general effect of an increase in SC on WTE was negative, meaning that drivers were less willing to engage automated driving in more complex situations (reflecting an increase in driving task demands), while the effect on WTRC was the opposite. Although no other studies that investigated WTE or WTRC in Level 3 automated vehicles were identified, these findings are supported by Puga (2016) who reported an increased willingness to use ACC in less complex driving conditions.

There was a significant effect of speed observed only during automated drives. During automated driving, higher speed (90 km/h) increased the odds of WTRC. This result can be explained by the comparison of driving task workloads during automated driving and manual driving. As discussed previously, the driving simulator was not validated for speed. Deficiencies in the perception of absolute and to a lesser extent, relative speed may have minimised the effect of the speed difference. It was concluded that, since drivers were relieved of vehicle manoeuvring task during automated drives, they had more internal resource available (Yamani & Horrey, 2018) and were able to perceive and process the difference between the high speed and the low speed.

6.4.2 Perception of safety

Effect of situation complexity

A strong effect of situation complexity on POS was observed with high SC resulting in lower POS. This finding was indirectly supported by Fuller et al. (2008) who suggested that feelings of risk can behave as a surrogate for driving task difficulty. Since measurement of safety is often opposite of the measurement of risk (B. Wang et al., 2002), it can be concluded that POS decreases with an increase in driving task difficulty. All four high-complexity events recorded significantly lower ratings of POS in comparison with the low-complexity event (Free). A possible correlation/association between SC and POS for individual events was suggested.

The parameter estimates of POS for events indicated that the event yielding the lowest POS rating was RF. This event exposed participants to a situation where visibility was suddenly restricted and road conditions deteriorated making the driving task more demanding. In an attempt to compensate for possible speed adaptation behaviour in manual drives (de Craen et al., 2008), participants were instructed to adhere to the speed limit as long as they felt comfortable. Therefore, it was not surprising that the reduction in POS, in comparison to the low-complexity event, was so significant since many participants tested their limits of comfort and demonstrated speed adaptation behaviour. The event with the second-lowest mean POS score was the OC (oncoming car). This event exposed drivers to a latent hazard situation where most of the response was outside the driver's control. The drivers may have recognised the potential hazard but there was little time to react and a very limited range of responses. The next lowest POS was recorded for the GW (give way) event. This event, despite implied complexity, was entirely under the driver's control in manual driving mode and therefore resulted in higher POS than what was observed at RF (rain and fog) and OC events. The highest POS among high-complexity events was recorded for the VF (vehicle following) event. Similar to the GW event, the driver in manual driving mode was entirely in control despite being forced to experience potentially uncomfortable time headway. It can be speculated that the timing of the question point within the VF event was responsible for such a relatively high POS. The question point for the VF event occurred after approximately 30 seconds of steady time headway. Therefore, participants had time to become accustomed to the new driving conditions potentially resulting in higher POS than at the beginning of the event.

Effect of driving mode

The POS during automated driving was higher than the POS observed during manual driving. The effect was statistically significant although not large. During manual drives, participants had to control a relatively unfamiliar vehicle while compensating for limitations in the simulation visuals. In comparison, during automated drives participants were relieved of these tasks. It could be assumed that automated driving presented lower driving task demands compared to manual driving. They found that for automation-inexperienced drivers, the perceived driving workload was similar for both driving modes. As the majority of participants in Study 3 were automation-inexperienced it was no surprise that the difference in POS was relatively small. However, the effect was statistically significant suggesting that the automation was successfully presented as confident, assured and steady driving in terms of longitudinal and lateral control resulting in slightly higher POS. A similar observation based on a study of effects of ACC (adaptive cruise control) was made by Marsden et al. (2001) who reported that more homogenous speeds achieved by ACC, contributed to better traffic safety.

The effect of driving mode on POS was further examined by observing interaction parameter estimates for individual events (driving mode*SC). They revealed that driving mode made a significant difference only at the VF event and to a lesser extent at the GW event. In both events, POS was higher during automated driving. There was no significant difference in POS for the other three events (Free, OC and RF). However, such a result for the VF event was in contrast with Siebert et al. (2017) who investigated drivers' experience of risk and comfort and found that there was no significant difference between THs of self-driving and distance-assisted driving. However, Siebert et al. (2017) study scenarios were made of sequences of vehicle following, instead of continuous and more naturalistic drives presented in Study 3. It was concluded that the difference in POS for the VF event was the result of the compensatory speed adaptation adopted by some participants during manual driving and limited absolute speed perception in the simulator. Since the VF event exposed participants to the TH locked at 1.5 seconds, higher driving speed corresponded with a longer headway. Therefore, any reduction in speed during manual driving resulted in a shorter headway. In combination with the lack of accurate speed perception and difficulty in maintaining a constant speed, some participants reacted by slowing down. In several cases, the event ended due to minimum allowed speed being reached. The reduction in speed led towards a further increase in driving task demands and lower POS. In contrast, as long as the speed was maintained there was no decrease in headway. The automated driving style was assured and homogenous with minimal variations in speed preventing such decrease in POS. To most participants, especially ones who did not manage to fully master manual control of the simulated vehicle, the GW event was presented with better timing and confidence during automated drives. Therefore, observed higher mean POS of automated drives for these events is not surprising. There was no significant interaction for all other events (Free, RF and OC), where the observed variations of travel speed were generally small.

Effect of speed

Driving speed did not have a statistically significant effect on POS. However, the observed direction of the speed was as hypothesised given that POS was slightly higher at a lower speed. It is anticipated the effect of higher speed reflecting an increase in driving demands would be more pronounced if drivers were able to more accurately perceive the absolute speed. Examination of parameter estimates for the interaction of speed and SC (situation complexity) revealed that the effect of speed was significant only for Free driving event and marginally significant for OC (oncoming car) event. As the Free event represented a low SC with minimal driving task demands, it was concluded that participants were able to dedicate more resources towards observing speed and experience the effects of the relative difference between speed conditions.

Apart from the free driving event, POS was reduced at the higher speed for the RF and the OC events. The high-speed condition resulted in a small increase of POS for VF and GW events. The effect on POS for GW and VF events was smaller and less significant than for other events. The simplest explanation in the case of the GW event could be that participants needed to slow down before entering the intersection, therefore, eliminating the difference in speed. Similarly, for the VF event, the simple explanation is that participants were influenced by the fixed time headway that was maintained at 1.5 seconds. Therefore, the driver's relative perception of speed was likely absorbed in variations of distance headway. A small increase in POS is probably a product of a confounding effect due to visual differences in driving environments used to present different speed conditions. Therefore, it can be concluded that both GW and VF events were inherently insensitive to the relative speed differences.

6.4.3 Preference for the driving mode

The driving mode preference was derived as a unifying variable that bridged the two driving modes, manual and automated, as WTE could be observed only during manual drives and WTRC only during automated drives.

The significant effect of SC on preference was not surprising since the dependent variable was derived from WTE and WTRC, both strongly affected by the level of SC. Overall, participants prefer manual vehicle control mode when facing a more complex situation. Interestingly, the preference for manual control was the highest for events that can be classified as less predictable and not completely under the driver's control (OC and RF). Unlike VF and GW events, where the driver perceives enough information about the situation to react, OC and VF events deliver incomplete information sets, forcing the driver to take some risks. This suggests that certainty might play an important role in the preference of vehicle control mode. For example, visibility is reduced in the RF event, denying driver information of what is beyond this range. In the OC event, the driver is denied certainty about thr overtaking car's intentions.

Also, there was a statistically significant increase in the preference for manual driving mode for the high-speed condition. The main effect of the driving mode was not significant; however, several interesting observations were made after examining parameter estimates for the interaction between driving mode and SC for each event. Two of the events, the RF (rain and fog) event and the OC (oncoming car) event revealed a statistically significant interactions with driving mode. In the case of the RF event, drivers preference for manual vehicle control more was more likely to be lower when experiencing this event during automated driving compared experiencing it during automated driving. It was concluded that majority of participants accepted that automated system was capable of handling on-road conditions. During the RF event, the automated system maintained the same speed under the assumption that functional automated vehicle would be equipped with a range of sensors capable of ”seeing and feeling” the road better than human drivers. For example, thermal imaging has the potential to penetrate fog further than visible light cameras (FLIR, 2020) in addition to other sensors (e.g. road friction) and technologies (e.g. near-field communication) that might be employed in future automated vehicles. This example emphasised the importance of training and exposure to the use of automated driving.

An even stronger effect of driving mode was observed for the interaction with the OC event. When the OC event was experienced during automated drives the preference for manual vehicle control was likely to be significantly higher compared to such preference observed during manual driving. This suggests that participants disagreed with how automated system reacted to this situation. A feasible explanation could be that when experiencing an increase in driving task demands, drivers would attempt to compensate by reducing speed (Jeihani & Banerjee, 2018) while when the OC event was encountered during automated driving the speed was not reduced.

6.4.4 Association of perception of safety and WTE/WTRC

This test confirmed that POS and WTE/WTRC had a very strong association. The effect of WTE on POS was positive, meaning that higher WTE would be more likely associated with higher POS. The effect of WTRC was negative, meaning that higher WTRC would be most likely associated with lower POS. Therefore, it was concluded that POS can be used as a predictor of a driver’s WTE/WTRC. Although no comparable studies that measured POS in AVs (automated vehicles) were found, some similarities can be identified with the results of surveys on AVs. Assuming that measurement of safety is opposite to measurement of risk (B. Wang et al., 2002), the association of POS and WTE/WTRC was indirectly supported by Ward et al. (2017) who found that risk perception had a significant impact on interest in using an automated vehicle.

6.4.5 Effect of demographics categories and attitudes on WTE/WTRC

Data collected in the Demographics questionnaire can be divided into two groups. The first group of questions observed effects of objective categories such as gender age, driving experience, number of kilometres driven per week and details about participant’s car on WTE/WTRC. The second group of questions attempted to examine the effects of attitudes on WTE/WTRC observed in the form of self-perceived skills, safety and technology acceptance.

When exploring the effects of driver characteristics on WTE/WTRC, due to the uniqueness of the dependent variables, it was not possible to directly compare results with the findings from the literature. Indirectly, results were compared with outcomes of surveys on the perception of automated driving. Some conclusions could have been derived and in general, agree with the observed effects. Trust in automation and driving enjoyment were significant predictors for both WTE and WTRC. The number of kilometres driven per week was found to be a significant predictor for WTE, and car transmission a significant predictor for WTRC. The results of the regression analysis should be considered with a level of caution due to the relatively small sample size use, which contained unbalanced gender and age distributions.

Trust in automation

As hypothesised, a higher level of trust in automation predicted an increase in WTE. Reversely, the same increase in the level of trust in automation predicted a reduction in WTRC. Molnar et al. (2018) reported similar results in the study where vehicle control preferences were significantly related to the reported trust.

Driving enjoyment

The negative effect of driving enjoyment on WTE was expected, however, the strength of the effect in comparison with the effect of trust in automation was a surprising finding. Hohenberger et al. (2016) reported a similar finding of a negative effect of pleasure on willingness to use automated cars. Kyriakidis et al. (2015) analysed survey data and concluded that drivers who enjoyed driving were more likely to prefer a manually controlled car. The positive effect of driving enjoyment on WTRC was also very strong but not as strong as for WTE. Hartwich et al. (2018) confirmed the importance of driving enjoyment for the acceptance of automated driving. However, they investigated enjoyment experienced during automated driving, not the self-reported participant attitude (from drivers who previously never experienced automated driving). Johnsen et al. (2017) observed that the shift of the driving task from the driver to the automated system was not always perceived as a benefit due to the loss of joy of driving.

Number of kilometres per week

The number of kilometres driven per week had a strong positive effect on WTE. This finding was relatively easy to explain. Drivers who drive a lot are more likely able to see and appreciate the benefits of automated vehicle control. This was supported by Kyriakidis et al. (2015) who concluded that the time spent in the vehicle was a significant positive factor in adopting automated vehicles.

Manual car transmission

Having a car with a manual transmission had a significant positive effect on WTRC. It was not surprising that drivers of manual cars were more willing to resume control of the car as the preference for manual transmission suggests the internal locus of control in the context of driving. This was difficult to support by previous research as there were very few publications on the effects of manual transmission. This was not surprising since in the framework of automated driving AVs are seen as electric, making transmission redundant. However, both negative and positive effects of manual transmission have been reported. For example, Selander et al. (2012) found that older drivers benefited from driving a car with the automated transmission while Cox et al. (2006) found that young drivers with ADHD drove safer with manual transmission.

Attitudes

Attitudes towards technology in cars, being an early adopter of technology, being a safe driver and self-confidence did not have a significant effect on WTE/WTRC. A similar observation was made by Molnar et al. (2018) when examining whether engagement in technology was associated with the choice of automated driving mode.

6.4.6 Practical implications of study 3 findings

Several practical implications for the acceptability of the AVs were identified. Findings, such as effects of driving mode in the rain and fog conditions emphasised the importance of education and training before using AVs. Drivers need to know what AVs can and cannot do and to be trained to accept AV behaviour. Driving in more complex situations could benefit the most from automation since the processing and reaction times of an automated system are much quicker than human reactions and advanced sensor technologies are able to gather more information than a human driver. Also, this information (what the system sees and plans to do) needs to be conveyed to the human driver in real-time. This would provide a more complete information set compensating for uncertainty and generate trust and confidence in automation. This will be a task for HMI designers.

Since it was observed that the effect of automated driving style influenced several test outcomes, some level of individual customisation would be necessary for Level 3 AV driving style, and to a lesser extent in higher levels of vehicle automation. The driver's comfort will have an important role in the acceptance of

AVs. It is quite possible that some, most likely older drivers wouldn't be able to adapt to certain aspects of high-level automation driving, for example platooning with extremely short time headways. As POS had a strong association with WTE/WTRC, the automation system needs to prevent or moderate all driving situations that may lead towards subjectively high POS to facilitate acceptance of automated vehicles.

6.4.7 Recommendations for future research

The effects of speed on patterns of the selection of AV control mode would be more effectively explored in a higher-fidelity simulator, that has been validated for absolute speed perception. The effects of automated driving style on a driver's willingness to use automated driving mode need to be further explored due to issues of driver comfort and motion sickness. Although an ordinal scale for WTE/WTRC was selected for both Study 1 and Study 4, a linear scale (similar to one for POS) for recording WTE/WTRC scores would allow a more precise statistical analysis of several hypotheses on WTE/WTRC.

The strong effect of driving enjoyment suggested that this topic is highly relevant for the adoption of AVs and should be investigated in simulator studies rather than using surveys. Johnsen et al. (2017) too, concluded that the impact of driving enjoyment on acceptance of AVs requires further research. Related to this issue, mechanisms of how enjoyment was derived from driving were not well researched as demonstrated by the scarcity of publications. Also, it is recommended that a driving simulator study with targeted age or driving experience groups, be undertaken to identify the effects of specific driver characteristics on acceptance of AVs.

6.4.8 Study limitations

Several limitations were identified in the course of the study and data analysis however, despite these limitations, it was concluded that none of the main findings was significantly affected. The simulator was not validated for the absolute perception of speed. Regardless, speed was included as one of the independent variables of the study design in the hope that relative speed difference would be easily perceived. Also, restricted FOV (field of view) and inaccuracies in image geometry and differences in the surrounding environments might have influenced results for some of the scenario events. The effect of driving speed was generally obstructed by the inability of the simulator to deliver effective representations of absolute and relative speeds; however, it was possible to observe the effect of speed during the low complexity event. Supported by findings from the literature, it is expected that if speed was accurately represented in the simulator, the increase in speed would be reflected as a decrease in POS, and likely decrease in WTE and increase in WTRC for the majority of participants. Another simulator fidelity-related limitation was lack of a motion. Due to pre-existing technical issues, the motion base was substituted with transducers that were producing tactile vibrations.

Despite having a practice in entering ratings using the tablet, it became apparent that although convenient, the tablet-based data collection method was not perfect and, as a result, there is a possibility that occasional errors when entering ratings were made by participants. Indeed, a couple of older participants indicated that they struggled with using tablet for data collection. Another couple of participants indicated that they made a mistake when entering their ratings. These issues were addressed immediately. Older participants were allowed to give their ratings verbally while the researcher entered them on the tablet. All reported mistakes made during the experimental drives were noted and corrected. The data were not taken out because these issues, once corrected, would have had very little, if any, impact on the actual responses.

The participant sample size was relatively small for regression analysis

During data analysis, it became obvious that the VF (vehicle following) event could not be summarised and analysed with a single question point. In reality, the VF event can be broken into several segments, each segment with specific driving task demands. Up to a certain extent, other high-complexity events could be deconstructed into multiple segments as well. It has been concluded that consistently successful engagement in the VF event was difficult to achieve in manual control mode under the pretence of everyday driving. It is generally much easier to present short time headway as an isolated driving task such as in Siebert et al. (2017).

Most of the above limitations will be addressed in Study 4 such as omitting speed as an independent variable, simplifying the experimental task and identifying different phases of events.

6.4.9 Conclusions

The study attempted to explore the effects of external factors and driver characteristics on WTE or WTRC and associated POS in the context of non-critical situations during Level 3 automated driving.

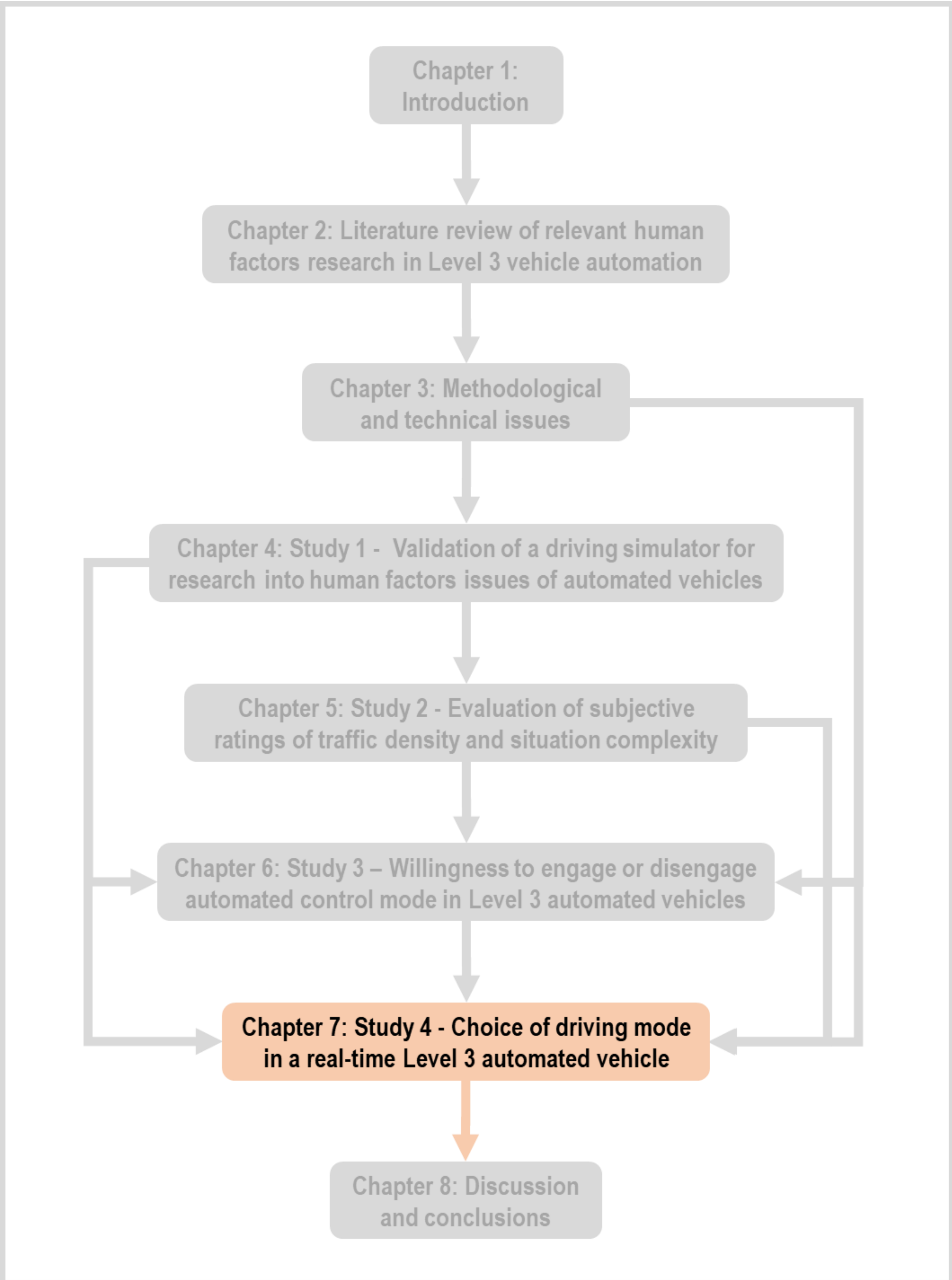
The study confirmed that the level of driving task demands is a very strong predictor of WTE/WTRC and subjective POS in Level 3 automated vehicles. The levels of driving task demands were derived by exposing participants to different combinations of situation complexity, driving mode and speed. Situation complexity, presented in the form of five different events, was found to be the most significant factor in the determination of WTE and WTRC. Relative POS ratings were established for each of the five events. The driving speed and driving mode did not have an overall strong effect except for several interactions. POS and WTE/WTRC demonstrated a strong association (positive for WTE and negative for WTRC) suggesting that POS could be used as a reliable predictor of WTE/WTRC. This finding means that surrogate variables, such as the feeling of risk (being the opposite of perception of safety), could be used in the exploration of choice of driving mode in Level 3 automated vehicles.

The investigation of the effect of driver characteristics found that, among observed attitudes, self-reported trust in automation and driving enjoyment were strong predictors for WTE/WTRC. These two categories generally had the opposite effect on WTE and WTRC. A higher level of trust in automation appeared to indicate higher POS and increased likelihood of using automated driving, while a higher level of driving enjoyment indicated lower POS and preference for manual driving.

Study 4 guidelines

The findings from Study 3, together with findings from Study 1 and Study 2, were used in the design of Study 4 as documented in Chapter 7 of this thesis. As described above, Study 3 used a simulator freeze technique to collect self-reported subjective measures while Study 4 observed actual driving behaviour in a real-time automated simulator vehicle. Therefore, Study 4 aimed to expand the investigation of choice of the driving mode in Level 3 automated vehicle under more naturalistic driving conditions.

CHAPTER 7



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Chapter 7 Study 4: Choice of driving mode in a real-time automated vehicle

7.1 Introduction

This study, Study 4 of the research project, was preceded by three studies. Study 1 provided validation of the driving simulator, Study 2 identified the appropriate experimental conditions and independent variables for subsequent studies and Study 3 incorporated all relevant findings of previous studies and explored the WTE (willingness to engage automation) or WTRC (willingness to resume manual control) under a variety of driving conditions. As Study 3 was based on self-reported behaviours, that do not always reflect actual driving behaviour, Study 4 was undertaken to observe real-time driving behaviour in a real-time Level 3 automated vehicle.

7.1.1 Background

Self-reporting is a relatively simple way of obtaining information about driver behaviour. The common methodologies, such as questionnaires and focus groups are inexpensive and can provide a large variety of data and it is not surprising that such a plethora of research on automated driving is based on this methodology. However, there is uncertainty as to the level at which self-reported driving behaviour reflects actual driving behaviour. Albert et al. (2014) compared data on the driving behaviour of young drivers obtained by vehicle data recorders with self-reported data. They found a high correlation between self-reported and recorded driving exposure. However, participants perceived themselves as safer drivers than what recorded data indicated. Zhao et al. (2012) investigated the relationship between self-reported aberrant driving behaviours and actual behaviour observed in the on-road study and found questionnaire scores to be related to some basic behaviours. Martinussen et al. (2017) assessed the driving skills of young male drivers by comparing self-reported (questionnaire) data with measured performance data in a driving simulator. They found self-assessment to be inconsistent and variable with driving skill, experience and sensation-seeking propensity. Self-assessed hazard perception and detection skills were the most inaccurate. Taubman-Ben-Ari et al. (2016) examined associations between self-report and objective measures of risky behaviour of young drivers. They concluded that self-reported measures were a reliable tool for the assessment of driving behaviour. In the case of older drivers, Blanchard et al. (2010) similarly compared self-reported and actual recorded driving data. They found self-estimated travelling distances to be inaccurate and driving in challenging situations to be under-reported. Molnar et al. (2013) made similar conclusions when comparing self-reported and objective driving measured in the study on the process of self-regulation among older adults.

These examples illustrate some of the complexities of the relationship between self-reported measures and observed measures. Bailey and Wundersitz (2019), in their review of the relationship between self-reported and actual driving-related behaviours, identified the *"lack of due diligence by researchers on relation to the format and context of self-reporting questions"* as the most serious issue (p. 3). They compiled a set of guidelines to improve the accuracy of self-reporting. Therefore, it was concluded that the observation of actual driver behaviour was a necessary step in the exploration of driver behaviour in automated vehicles.

As mentioned in previous chapters, the overall research assumed that in the foreseeable future, all new vehicles would be fitted with Level 3 automation capabilities and that mainly everyday driving was represented in the experimental drives. The main methodological feature of Study 4 was the real-time interaction with Level 3 vehicle automation. In other words, participants were able to change the driving mode at any time, rather than just report a preference for a mode change. There are examples of driving simulator studies that utilised real-time interaction with vehicle automation. Jamson et al. (2013) examined activation and deactivation of highly-automated vehicle control in a simulator experiment on behavioural changes in varying traffic conditions. They observed an increase in engagement in the non-driving task with every increase in the level of vehicle automation. Hooft Van Huysduynen et al. (2018) conducted a driving simulator study in which participants could drive in automated mode or disengage the system. They investigated different reasons that made drivers disengage from automated driving that included both lack of trust in automation and a lack of driving enjoyment. In other studies (Molnar et al., 2017, 2018), participants were able to engage in automated driving mode when feeling comfortable to do so. However, changes to manual control were enforced in scenarios by pre-programmed take-over requests. Molnar et al. (2017) investigated human factors issues associated with the transfer of control from automated to manual driving to categorise age-related differences in behaviour finding that older drivers were more comfortable with relinquishing control of the vehicle. Molnar et al. (2018) explored the influence of trust on the acceptance of vehicle automation. They found a strong association between trust in automation and being comfortable with not being a driver and evidence that experience of automation in the driving simulator to be an important contributor to the acceptance of this technology. Neubauer et al. (2012) used voluntary engagement in automated driving in the study of stress, fatigue and workload. They found that the availability of automation did not help in reducing fatigue and the stress induced by monotonous driving.

Exploration of vehicle automation in the context of everyday driving appeared to be a less common topic. Bellem et al. (2016) observed everyday, comfortable and dynamic driving in the simulator to establish metrics for the development of comfortable automated driving. In their simulator-based investigation of adaptive HMI for partial automation, (Ulahannan et al., 2020) presented everyday driving in a form of steady automated driving on a regular route. Neubauer et al. (2012) presented monotonous driving to participants to explore the effects of automation on stress, fatigue and workload. To some extent, Jamson et al. (2013) presented everyday driving although participants were allowed to freely engage in secondary tasks. The use of automation was voluntary; however, participants were instructed to engage automation as soon as they were comfortable to do so. Körber et al. (2018) used two non-critical situations in their study on the influence of trust promoting on reported trust, reliance behaviour and take-over performance in Level 3 automated vehicle. They found that that individual trust influenced environment monitoring during involvement in non-driving tasks.

In summary, given the uncertainties associated with self-reporting, actual driving behaviour was used in this study. Participants were exposed to quasi-naturalistic driving in a real-time interactive Level 3 automated vehicle simulator, and their choices of vehicle driving mode during non-critical driving events were observed.

7.1.2 Independent and dependent variables to be tested

The same five scenario events used in Study 3 were selected as the main events in Study 4. These events represent a relatively diverse set of driving situations with different levels of SC (situation complexity) and different levels of subjective POS (perception of safety). Using the same events under real-time conditions offered several advantages. These events have already been constructed and it was a relatively simple process to incorporate them into new scenarios. These events have been analysed in study 3, therefore, their effects on the selection of automated control mode were better understood. For example, the analysis of events identified that some events such as the VF (vehicle following) event were made of several different segments and that each segment should be observed separately in terms of selected vehicle control mode.

Independent variables

The selection of independent variables was guided by the adaptation of JCTF (joint conceptual theoretical framework), the literature review, the findings of previous studies and methodological constraints. As this study was informed by Study 3 findings, a similar set of independent variables was used where possible. The three independent variables used in the design of Study 3 were vehicle control mode, speed and situation complexity. The driving mode was not used as an independent variable since the vehicle control mode was decided by participants. Since the findings of Study 3 showed that the effect of speed on WTE during automated driving was not statistically significant, speed was not used as an independent variable in the current study. Therefore, only one type of driving environment was selected for all experimental scenarios. This was a rural road with a speed limit of 70 km/h with a combination of straight sections, left bends and right bends. It also contained several intersections and a roundabout. The following independent variables were chosen for the study: situation complexity, perception of safety, starting vehicle control mode, the procedure of selecting vehicle control mode and exposure to Level 3 automated driving.

SC (situation complexity) was shown in Study 3 to be a major contributing factor for predicting WTE and WTRC. It was also easy to manipulate the level of SC in the simulator. Therefore, SC was selected as the main independent variable used in the current study, with the Free (free driving) being classified as low complexity event and the other four main events classified as high complexity events.

A strong association between the POS and the WTE/WTRC was confirmed in Study 3. Since average POS for each of five events was measured in Study 3 it was possible to classify each event within two levels of POS, high and low. Therefore, POS was selected as an independent variable.

The starting driving mode was chosen as an additional independent variable. Although participants were able to select preferred vehicle control at any time during the drives, the aim was to observe possible effects of initial control mode on continued driver behaviour during the experimental drives.

The independent variable representing the procedure of selecting vehicle control mode intended to explore whether there was a difference between results obtained during simulation-freeze (forced-choice) drives and results obtained during uninterrupted driving (free-choice). In both methods, participants faced the same driving situations and made choices of vehicle control mode. However, in forced-choice drives, participants would face decision points where they would need to select and proceed driving in a control mode until the next decision point.

Study 4 presented a real-time interactive experience of a simulated Level 3 automated vehicle to participants. Therefore, changes in attitudes towards vehicle automation, levels of acceptance and understanding of vehicle automation were evaluated with a comparison of a questionnaire administered before exposure and an identical questionnaire administered after exposure to experimental drives.

Dependent variables

During experimental drives, all simulator vehicle (driver) data were recorded in a binary replay file including the status of engaged driving mode. The selected driving mode was either manual or automated. Therefore, all dependent variable resulting from simulator drives were derived from these time series. Two dependent variables were derived from the time series of driving mode status. They were PAC (the proportion of automated control mode choices) and PAD (the proportion of time spent in automated driving mode).

Participants in Study 4 completed two free-choice drives. During each of these drives, they encountered five main events. For each of these events, their choices of vehicle control mode were observed and counted across all participants and both drives. The final counts for each event, therefore, represent how many times all participants in both drives used vehicle automation and how many times they manually controlled the vehicle. The resultant PAC scores for each event were calculated as the proportion of automated vehicle control mode choices:

$$PAC_{Event} = \frac{Sum\_of\_automated\_choices_{Event}}{Sum\_of\_automated\_choices_{Event} + Sum\_of\_manual\_choices_{Event}}.$$

Similarly, PAD for each event was calculated for entire two experimental drives as a proportion of total drive time spent in automated driving mode across all participants. Molnar et al. (2018) used a somewhat similar measure, the proportion of manually driven simulator scenarios.

The second group of dependent variables were addressed with questions in the pre-drive and the post-drive automation questionnaires that intended to observe the effects of exposure to vehicle automation. They were preferred level of vehicle automation, intended frequency of automation use and preference of vehicle control mode in different driving situations.

The observed change in participants' opinion of their preferred level of vehicle automation (ranging from no automation to full automation) after exposure. This was not limited to a particular level of vehicle automation.

Participants were asked to anticipate how often they would use the automated control mode in a Level 3 automated vehicle on a linear scale from 0 to 100 where 0 represented a complete rejection of automated driving and 100 use of automated driving mode whenever possible.

Participants were also asked to provide their preference of vehicle control mode for a range of different driving situations. The linear scale from 0 to 100 was used where 0 represented maximum preference for manual control mode and 100 maximum preference for automated control mode.

7.1.3 Study research questions

This simulator study was planned as a continuation of Study 3 in which a driver's choice of vehicle control mode in a Level 3 automated vehicle was explored using a self-report simulation freeze data collection methodology. The main data collection methodology for Study 4 was based on uninterrupted driving and real-time interaction with vehicle automation. The study aimed to answer the following research questions:

- What are the key internal and external factors that are influencing the driver's choice of control mode in Level 3 automated vehicles?
- How does a driver's choice of Level 3 automated vehicle control mode change when exposed to a range of driving situations resulting in different levels of driving task demands?
- How does exposure to automated driving affect drivers' perceptions of automated driving and intentions to use it?
- Does forcing the selection of vehicle control mode influence the choice of control mode in a Level 3 automated vehicle?
- Does WTE transfer to the actual choice of vehicle control mode in Level 3 automated vehicle?

7.1.4 Hypotheses

Building on the above-mentioned research questions, the main hypotheses for this study are presented in **Table 7.1**.

Table 7.1 *List of Study 4 hypotheses*

H#	Hypothesis
H7.1	Increase in the level of SC has a negative effect on PAC (the proportion of automated control mode choices)
H7.2	Increase in the level of POS has a positive effect on PAC
H7.3	Starting driving in automated mode has a positive effect on PAD (the proportion of time spent in automated driving mode)
H7.4	Exposure to automation increases preference for a higher level of vehicle automation
H7.5	Exposure to automation has a positive effect on the intention to use of automated driving
H7.6	Exposure to automation has a positive effect on the preference of automated driving in different situations
H7.7	Driver characteristics and attitudes can be used as predictors of PAD
H7.8	Driver characteristics and attitudes can be used as predictors of PAC
H7.9	Forcing choice of a driving mode vs free choice of a driving mode does not have an effect on the choice of vehicle control mode.

7.2 Method

7.2.1 Experimental design

The study was based on the repeated measures design with five independent variables. The independent variables were situation complexity, perception of safety, starting driving mode, the choice of the vehicle control mode and exposure to automation. The Study 4 independent variables are summarised in **Table 7.2**.

Table 7.2 *Study 4 independent variables*

Independent variables	Conditions	Description
Situation complexity (SC)	Low	Free (free driving) event
	High	RF (rain and fog), OC (oncoming car) , GW (give way) and VF (vehicle following) events
Perception of safety (POS)	Low	RF, OC, GW
	High	Free, VF
Starting vehicle control mode	Manual	Drive starts in manual control mode
	Automated	Drive starts in automated control mode
Procedure for selecting vehicle control mode	Free	Participants can change driving mode at any time
	Forced	Selection of driving mode required at 13 locations
Exposure to automated driving	Before	Questionnaire Before experimental drives
	After	Questionnaire After experimental drives

7.2.2 Participants

A total of 41 participants were involved in the study: 26 males and 15 females, ranging in age from 19 to 75 years, with a mean age of 37.42 years for males and 28.07 years for females. Participants were recruited from both Monash University (undergraduate students, post-graduate students and staff) and outside using personal contacts, MUARC (Monash University Accident Research Centre) participant database and advertising on social media. Participants were required to have either a full driver license or a P2 (second year probationary) license. They were also required to drive at least 5000 km per year. Ethics approval was obtained from the Monash University Human Research Ethics Committee. A small number of participants (5 out of 41) participated in both Study 3 and Study 4. However, since these studies were conducted one year apart (May 2018 vs May 2019) and the experimental task was different it is argued that any carryover effects would be negligible. Therefore, they were considered to be de-facto new participants.

7.2.3 Apparatus

Driving Simulator

The MUARC Automation simulator (**Figure 7.1**) is described in Chapter 3. The motion base was active during experimental drives in Study 4 producing three degrees of freedom of movement as well as vibration.

Figure 7.1 *Automation driving simulator*

In addition to standard simulator features, a real-time automated driving mode was developed for the study. The driver was able to switch between manual and automated driving modes by pressing an illuminated green button (**Figure 7.2**) located right of the steering wheel.

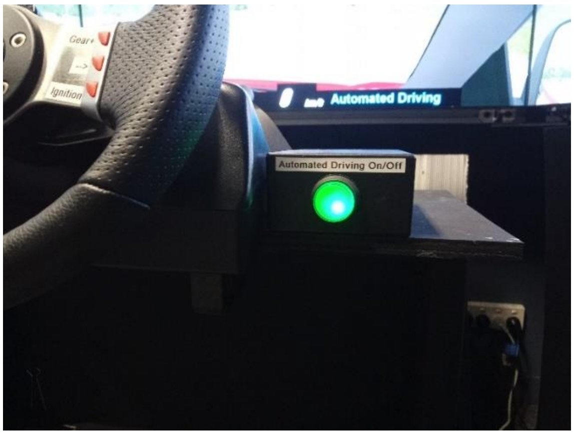


Figure 7.2 *Driving mode selection button*

The visual indication of the engaged driving mode was displayed on the virtual instrument panel. When the manual driving mode was selected "Manual Driving" was displayed on the bottom right side of the screen (**Figure 7.3a**) and when the automated driving mode was selected "Automated Driving" was displayed (**Figure 7.3b**). The design of the HMI is discussed in Chapter 3 of this thesis.

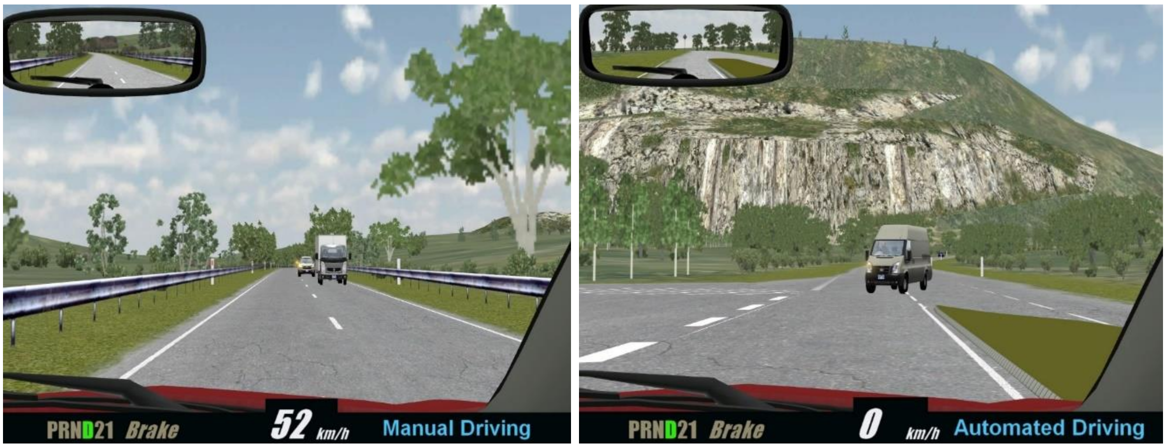


***Figure 7.3** An example of **a)** Manual driving mode and **b)** Automated driving mode*

Electronic questionnaires

A PC was used for collecting questionnaire data. Qualtrix software was used for the development and administration of the questionnaires. After collection, the data were exported in the form of a spreadsheet and processed for data analysis.

7.2.4 Experimental scenarios

Four simulator scenarios were developed for the study. A country environment was selected for all scenarios. The speed limit was set at 70 km/h with an exception of a short section of winding road where the speed limit was reduced to 50 km/h. The road consisted of an undivided single lane in each direction. The first two simulator scenarios were free-choice drives. They contained the same five main events, although presented in a different order.

Scenario 3 and Scenario 4 represented a "Forced-choice" drive. The only difference between these scenarios was in the instruction displayed during forced decision points. Scenario 3 listed automated choice first while Scenario 4 listed manual choice first. General characteristics of experimental scenarios are summarised in **Table 7.3**.

***Table 7.3** Study 4 simulator scenarios*

Scenario	Choice of driving mode	Difference between scenarios
1	Free-choice	Order of five main events
2	Free-choice	
3	Forced-choice	Automated choice listed first
4	Forced-choice	Manual choice listed first

Free-choice scenarios

The five main events of free choice scenarios were the GW (give way), the RF (rain and fog), the Free (free driving), the VF (vehicle following) and the OC (oncoming car) event. The order of events in each scenario is summarised in **Table 7.4**.

Table 7.4 *Order of events in free-choice scenarios*

Scenario	Event 1	Event 2	Event 3	Event 4	Event 5
1	GW	RF	Free	VF	OC
2	OC	GW	RF	Free	VF

These events were replicated from the events used in Study 3 (see Chapter 6, section 6.2.4). The only noticeable difference between events of Study 3 and events of Study 4 was the type of intersection used in the GW event. The GW event from Scenario 1 and Scenario 2 is illustrated in **Figure 7.4**. However, there were no fundamental differences in driver's task as a result of engagement in this event as the number of vehicles used in the event and time gaps were equal in both Study 3 and Study 4. As in Study 3, there were one low complexity event (Free) and four high complexity events (GW, RF, OC and VF).

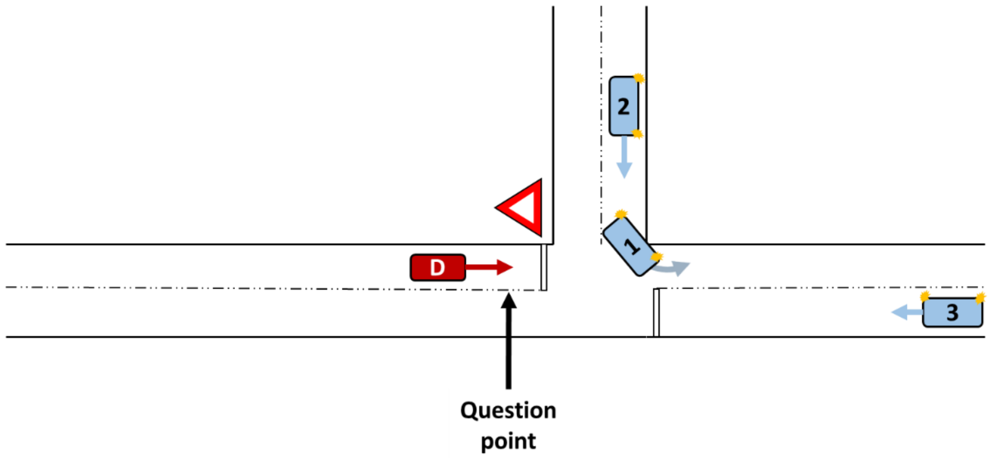


Figure 7.4 *GW event in free-choice drives*

For data analysis, selected vehicle control mode was observed at locations of question points of each event indicated in Study 3 except for the VF event which observed selected vehicle control mode at a different point for testing effects of SC as illustrated in **Figure 7.5**. Therefore, vehicle control mode was observed when the target TH (time headway) was initially established as SC was rated as high at that instance in Study 3.

At the end of the drive (determined by the endpoint of the scenario), one of two possible instructions was displayed on the screen. If the simulator car was in manual driving mode the displayed message was: "Please bring the car to the full stop." The drive ended when the car was stopped. If the simulator car was in automated mode the displayed message was: "Please resume control of the vehicle!". After the participant switched from automated driving mode to manual driving mode, the message: "Please bring the car to the full stop" would be displayed and the drive ended when the car was stopped.

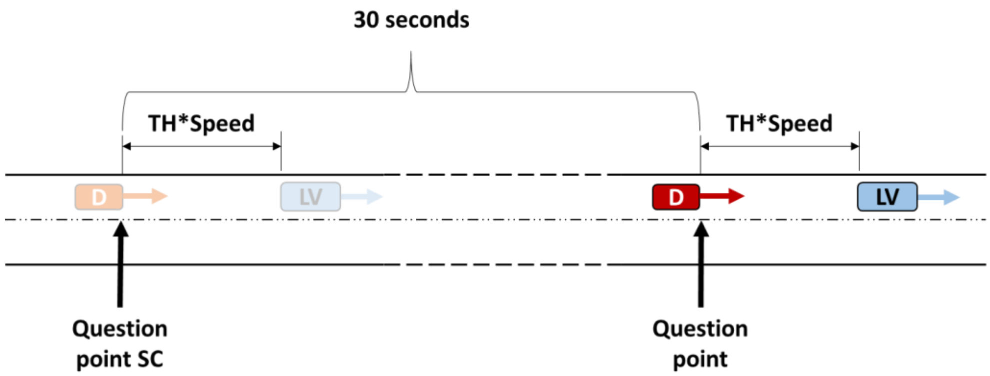


Figure 7.5 *Question points of the VF event*

Forced-choice scenarios

Scenario 3 and Scenario 4 were identical, the only difference being the instruction given to participants at each decision point. The instruction displayed in Scenario 3 was: “Please select driving mode: - Press Green button for Automated OR - Push Throttle pedal for Manual” (**Figure 7.6**). The instruction displayed in Scenario 4 was ”Please select driving mode: - Push Throttle pedal for Manual OR -Press Green button for Automated”.

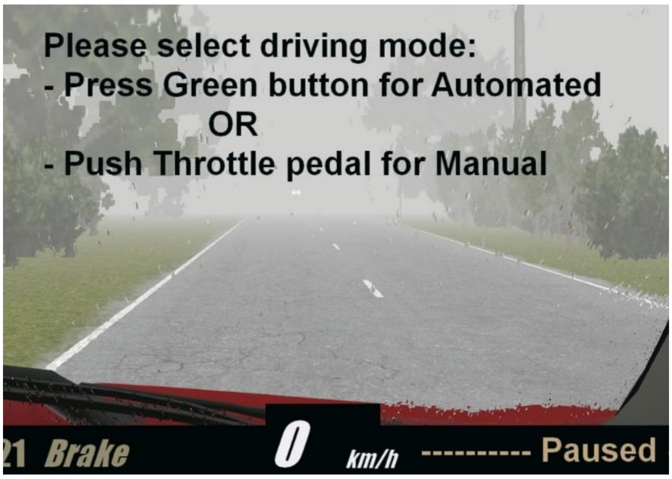


Figure 7.6 *Scenario 3 instruction*

In these scenarios, the simulation was programmed to freeze at 13 pre-determined decision points and instruct a participant to choose a vehicle control mode to continue driving. These points are listed in **Table 7.5**.

At points 1 and 2, drivers faced right and left bends respectively, while points 5 and 11 represented free driving on a straight road. The remaining decision points were located within the five main events that were part of free-choice scenarios. Each of these main events provided at least two decision points. The main five events were replicated from Study 3.

The GW (give way) event used in forced-choice scenarios happened at a roundabout. The two decision points associated with this event are illustrated in **Figure 7.7**. The first decision point (GW1) occurred at 40 meters before the stop line, the second decision point (GW2) just before the stop line.

Table 7.5 Decision points from Scenario 3 and Scenario 4

Point	Point code
1	RB (Right bend)
2	LB (Left bend)
3	RF1
4	RF2
5	Free1
6	VF1
7	VF2
8	VF3
9	OC1
10	OC2
11	Free2
12	GW1
13	GW2

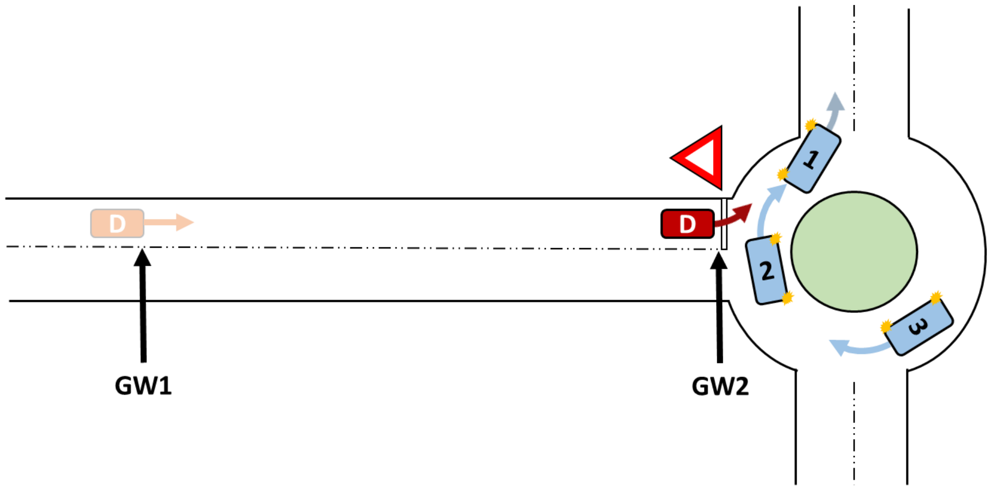


Figure 7.7 *Decision points from the GW event in Forced-choice drives*

The OC (Oncoming car) event was identical to the OC event from free-choice drives. Two driving mode selection points assigned to this event are illustrated in **Figure 7.8**. The first point (OC1) occurred at 50 meters distance between the driver (D) and truck (T). The second point (OC2) occurred at 10 meters between D and T.

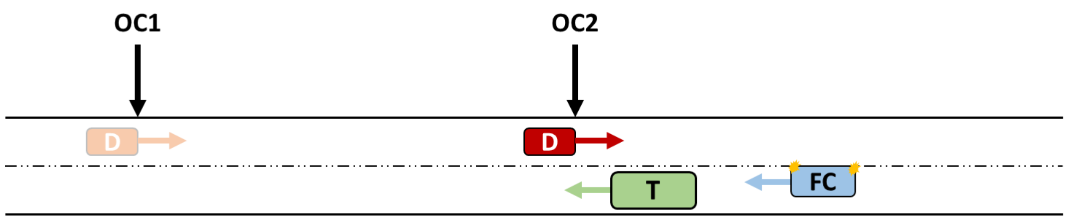


Figure 7.8 *Decision points from the OC event in Forced-choice drives*

Two driving mode selection points assigned to the RF (rain and fog) event are illustrated in **Figure 7.9**. The first point (RF1) occurred at the onset of rain and fog conditions. The second point (RF2) occurred after 20 seconds of driving in these conditions.

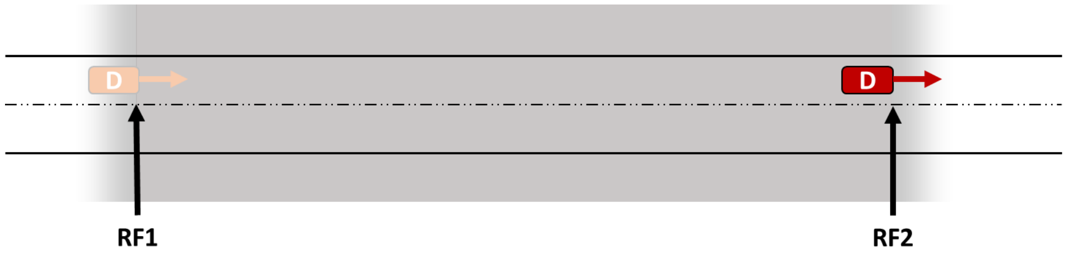


Figure 7.9 *Decision points from the RF event in Forced-choice drives*

The VF (Vehicle following) event was slightly different from the VF event used in free-choice scenarios as it included an additional segment. There were three decision points assigned to this event as indicated in **Figure 7.10**. For illustration purposes, time headways are represented as distances (TH multiplied by the speed of the driver).

The first point (VF1) occurred after the lead vehicle (LV) pulled out from the service station ahead of the driver (D). At this point, the driver was able to see that the distance between D and LV had been reducing. The second point (VF2) occurred when 1.5-second time headway (TH1) was established and maintained for 20 seconds. After the VF2 decision had been made, the headway between D and LV would gradually reduce TH to 0.5 seconds (TH2). The third decision point (VF3) occurred after TH2 was maintained for 20 seconds. After the selection has been made, the drive continued and LV gently accelerated to above the speed limit (90 km/h) and eventually disappeared from the view of the driver. If the driver (only in manual control mode) slowed down to under 30 km/h or attempted overtaking LV, the events would end and the question point would occur to prevent the driver from coming to a full stop. After the selection of the vehicle control mode has been done, LV gently accelerated to above the speed limit and disappeared from the view of the driver.

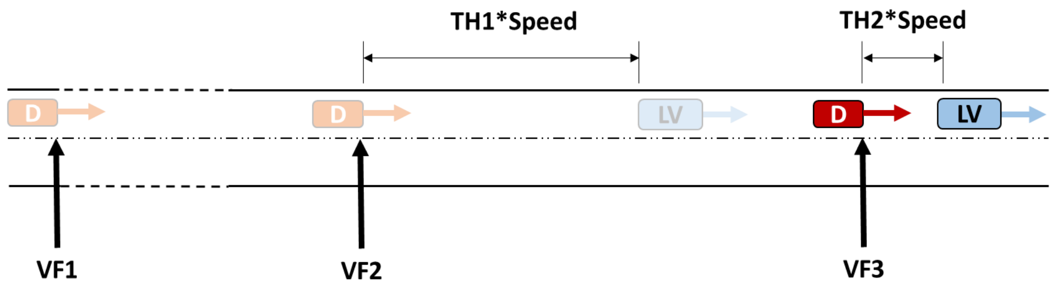


Figure 7.10 *Decision points from the VF event in Forced-choice drives*

Order of experimental drives

The order of experimental drives is illustrated in

Table 7.6. The first two drives were Scenario 1 and Scenario 2 in a counterbalanced order combined with the counterbalanced order of starting vehicle control modes. The third drive was either Scenario 3 or Scenario 4, The order of these scenarios in the third drive was counterbalanced between participants.

Table 7.6 Order of experimental drives

Drive	Choice of driving mode	Scenarios	Starting driving mode
1	Free-choice	Scenario 1 and Scenario 2 (counterbalanced order)	Manual and Automated (counterbalanced order)
2	Free-choice		
3	Forced-choice	Scenario 3 or Scenario 4 (counterbalanced order)	N/A

7.2.5 Collected data

Demographics questionnaire

Demographics questionnaire included questions about participant such as age, driving experience, attitudes towards vehicle automation and subjective perceptions of their driving skills. The demographics questionnaire is presented in Appendix C. The list of questions was identical to the one used in Study 3.

Automation questionnaires

Pre-drive and post-drive automation questionnaires were identical, apart from an additional (last) question in the post-driving questionnaire asking whether their opinion about vehicle automation has changed after the experimental session. The post-drive automation questionnaire is presented in Appendix D.

Simulator replay files

During each experimental simulator drive, a large number of parameters were recorded in binary replay files. The parameters that were used in data parsing (reduction) were road segment ID, driver speed and status of vehicle control mode. Data reduction was an intermediate step in obtaining information for further analysis providing dependent variables such as counts of automated and manual driving mode selections, PAD (proportion of automated driving) and PAC (proportion of automated control mode choices).

7.2.6 Procedure

The experimental session was conducted in the newly-constructed Automation driving simulator at Monash University Accident Research Centre. As in all simulator studies, participants were required to complete an informed consent form approved by the Monash University Ethics Committee and read the experimental instructions. They were then given a brief introduction to automated vehicles, different levels of vehicle automation with an emphasis on Level 3 automation and choice of control mode since they would be experiencing Level 3 automated driving in the simulator. Participants were then presented with a definition of willingness and an explanation of an experimental task. Participants were instructed that they were in a Level 3 automated vehicle capable of safely handling all situation presented in drives in automated control mode and that they could select a control mode they are comfortable with at any time.

This was followed by a demographics questionnaire that also included questions about driving habits, subjective driving skills, attitudes toward technologies and a series of questions about perceived safety in a variety of driving situations. Following this, a pre-drive automation questionnaire that contains questions about the preferred level of vehicle automation, intended frequency of automation use and preference of driving mode (manual vs automated) in a variety of driving situations.

Before the start of the experimental drives, a pre-drive well-being questionnaire was administered. After the Well-being questionnaire was completed participants were seated in the simulator and introduced to vehicle controls and interfaces. First, one practice drive was presented to familiarise participants with the simulator controls, visuals and switching between manual and automated modes. Once they demonstrated a good level of manual control of the vehicle, participants were asked to switch between manual and automated modes several times.

After a practice drive, two free-choice experimental drives were presented in a counterbalanced order. One of the drives would start in manual control mode and the second drive would start in automated control mode. During these drives, participants were able to switch between driving modes at any time. After completion of each drive, the simulator replay file was saved. Following free-choice drives, one forced-choice drive was presented. During this drive, the simulation would freeze at predetermined points and prompted the participant to decide which control mode driving mode will be used to continue driving. Once the mode is selected, it couldn't be changed until the next decision point.

After the end of the forced-choice drive, participants would leave the simulator vehicle and complete the post-drive Well-being questionnaire. This was followed by a post-drive Automation questionnaire which was identical to the pre-drive automation questionnaire with an additional question about change of their opinion of the automated vehicle. The total duration of the experiment was about 60 minutes. At the end of the session, participants were offered $20 for their participation and encouraged to make comments about the experiment. The study procedure is illustrated in **Figure 7.11**.

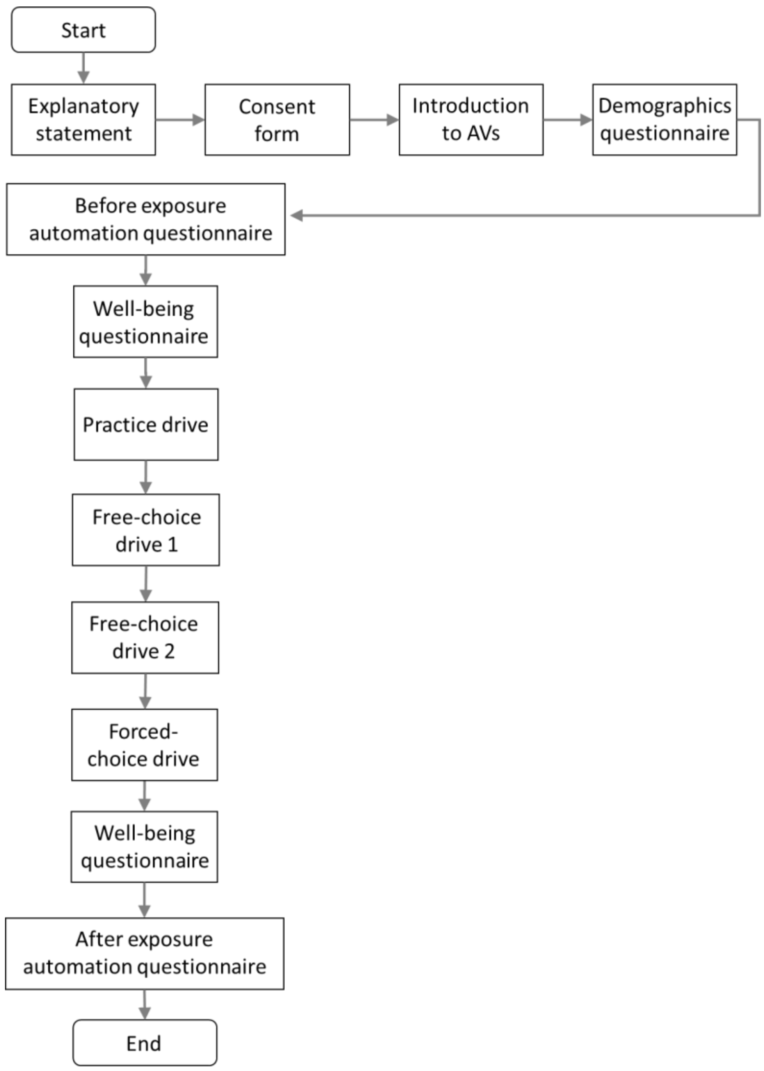


Figure 7.11 *Flowchart of Study 4 procedure*

7.3 Results

The statistical analysis was divided into four groups based on different datasets:

- Selection of vehicle control mode during free-choice drives,
- Effects of exposure to automation on perceptions and attitudes towards vehicle automation observed in automation questionnaires,
- Effects of driver characteristics and attitudes reported in the demographic questionnaires, on choices of vehicle control mode (PAD and PAC) and,
- Effect of type of choice (free-choice and forced-choice) on the selected driving mode.

7.3.1 Selection of vehicle control mode during free-choice drives

Effect of situation complexity on PAC

Situation complexity was used as an independent variable in statistical tests of hypothesis H7.1. The five scenario events consisted of one low SC (situation complexity) event and four high SC events. Scenario events, SC level, counts of manual driving mode choices and automated driving mode choices for each event across all participants and two free-choice drives and resultant PAC (proportion of automated vehicle control mode choices) are presented in **Table 7.7**. The resultant PAC score was the highest for the low-complexity (Free) event.

Table 7.7 *Counts of driving mode choices for each event and PAC scores*

Event	SC level	Manual choices	Automated choices	PAC score
Free	Low	26	55	.68
OC	High	34	46	.58
RF	High	35	46	.57
VF	High	37	41	.53
GW	High	41	40	.49

Chi-square tests were conducted for each high-complexity event to test the statistical significance of differences between PAC scores. The proportions of selected manual and automated vehicle control modes observed during high-complexity events were contrasted with the proportion of selected vehicle control modes observed during the Free event. The results of the tests are summarised in **Table 7.8**.

Table 7.8 *Summary of Chi-square tests results – effect of SC on PAC*

Event	Chi-Square	df	Asymp. Sig.
GW	12.745	1	.001
RF	4.588	1	.032
VF	8.418	1	.001
OC	3.971	1	.046

Chi-square goodness-of-fit tests indicated that there was a significant difference in PAC observed during all high-SC events (.58, .57, .53, .49 for GW, RF, VF, OC respectively) as compared with the PAC score of .68 observed for the Free event. Therefore, an increase in the level of SC had a negative effect on the choice of automated vehicle control mode.

Effect of perception of safety on PAC

The level of POS (perception of safety) was used as an independent variable for observing effects on PAC (proportion of automated vehicle control mode choices) to test hypothesis H7.2. The five scenario events of the free-choice drives were assigned of two levels of POS, low or high. These levels of POS were based on scores for each event observed in Study3. The Free and the VF events were associated with high POS while the remaining three events were associated with low POS. The VF (vehicle following) question point in Study 3 occurred when participants were already accustomed to a time headway of 1.5 seconds resulting in relatively high POS. Therefore, vehicle control mode at the VF event in free-choice drives was observed when participants were accustomed to the same time headway as well.

Events, POS levels, counts of manual and automated vehicle control mode choices, and PAC (proportion of automated mode choices) scores for each event are summarised in **Table 7.9**.

Table 7.9 *Counts of selected vehicle control modes and PAC*

Event	POS level	Manual choices	Automated choices	PAC score
Free	High	26	55	0.68
VF	High	28	49	0.64
OC	Low	34	46	0.58
RF	Low	35	46	0.57
GW	Low	41	40	0.49

The PAC score was the highest for the Free event followed by the VF event score. Chi-square tests were conducted for all events to evaluate the statistical significance of the difference between PAC scores. The proportions of manual and automated vehicle control mode choices observed during all events were contrasted with the proportion of vehicle control modes choices observed during the Free event. The results of the tests are summarised in **Table 7.10**.

Table 7.10 *Summary of Chi-square tests results – effect of POS on PAC*

Event	Chi-Square	df	Asymp. Sig.
GW	12.745	1	.001
RF	4.588	1	.032
VF	0.643	1	.432
OC	3.971	1	.046

Chi-square goodness-of-fit tests indicated that there was a significant difference in PAC observed during three low-POS events (.58 for OC, .57 for RF and .49 for GW) as compared with the value of .68 observed for the Free event. There was no statistically significant difference in PAC between two high-POS events, the VF event (.64) and the Free event (.68). Therefore, an increase in the level of POS has a positive effect on the choice of automated vehicle control mode.

Effects of starting vehicle control mode on PAD

The effect of starting driving mode on PAD (hypothesis H7.3) was analysed using the GEE method. The unstructured working correlated matrix was selected. For modelling the dependent variable, the linear model and identity link function were selected. The independent variable was starting control mode. The effect of driving mode on PAD (proportion of automated driving) was not significant ($\chi^2(1) = 2.92$, $p = .087$). Parameter estimates are presented in **Table 7.11**.

These results suggest that starting control mode of the free-choice experimental drive does not significantly affect the consecutive choices of the vehicle control mode during the drive. However, the observed PAD was marginally higher in automated starting conditions.

Table 7.11 *Parameter Estimates of Starting control mode - PAD*

Parameter	B	SE	95% Wald CI		Hypothesis Test		
			Lower	Upper	Wald χ^2	df	Sig.
Starting mode							
Automated	.054	.0445	-.008	.116	2.921	1	.087
Manual	0	.	.	.	.	.	.

7.3.2 Effects of exposure to automation

The results of the Automation questionnaires were used to test hypothesis H7.3. Participants were asked to complete the first Automation questionnaire before experiencing the simulator drives and the second Automation questionnaire after all simulator drives were completed.

Preferred level of vehicle automation

Following the introduction to automated vehicles, participants were asked to state in which level of automation they would be the most interested in. Participants were able to choose from no automation to full automation. The same question was presented in the post-driving automation questionnaire. Preferences before and after exposure to automated driving are illustrated in **Figure 7.12**.

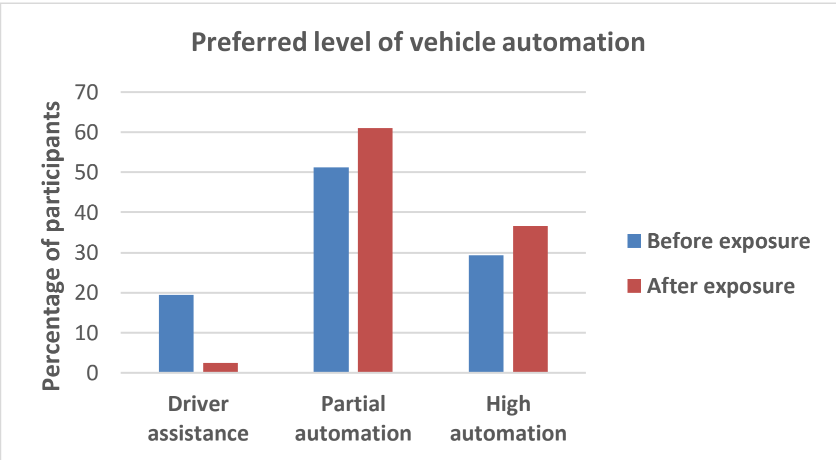


Figure 7.12 *Preferred levels of vehicle automation before and after experimental drives*

The effect of exposure to automated driving on participants' interest in the preferred level of vehicle automation (hypothesis H7.4) was analysed using the GEE method. The unstructured working correlated matrix, the ordinal model and the identity link function were selected. In this model, participants were the subject variable and exposure to automated driving (order of questionnaires) was the independent variable. The level of vehicle automation that participants were the most interested in using was the dependent variable.

The GEE test revealed a significant main effect ($\chi^2(1) = 4.658$, $p = .031$) of the order of questionnaires. This result suggests that as the result of exposure to automated driving in the simulator, participants significantly changed their opinion about vehicle automation and become more receptive towards higher levels of automation.

Parameter estimates for the effect of exposure to automation on the preferred level of vehicle automation are presented in **Table 7.12**. The relative odds ratio suggested that the probability of participants preferring a higher level of automation after being exposed to automated driving increased 1.86 times.

Table 7.12 *Parameter estimates for the main effect of exposure to vehicle automation on the preferred level of vehicle automation*

Parameter	Hypothesis Test			Exp(B)	95% Wald CI for Exp(B)	
	Wald χ^2	df	Sig.		Lower	Upper
Preferred level of vehicle automation						
Post-exposure	4.658	1	.031	1.864	1.059	3.282
Pre-exposure	.	.	.	1	.	.

Intended frequency of use of L3 automation

Participants were asked before and after the experimental drives about how often they would use automated driving if their car was equipped with Level 3 automation. The response was recorded on a sliding scale ranging from 0, for never, to 100 for whenever possible. Mean ratings of these scores are presented in **Figure 7.13**.

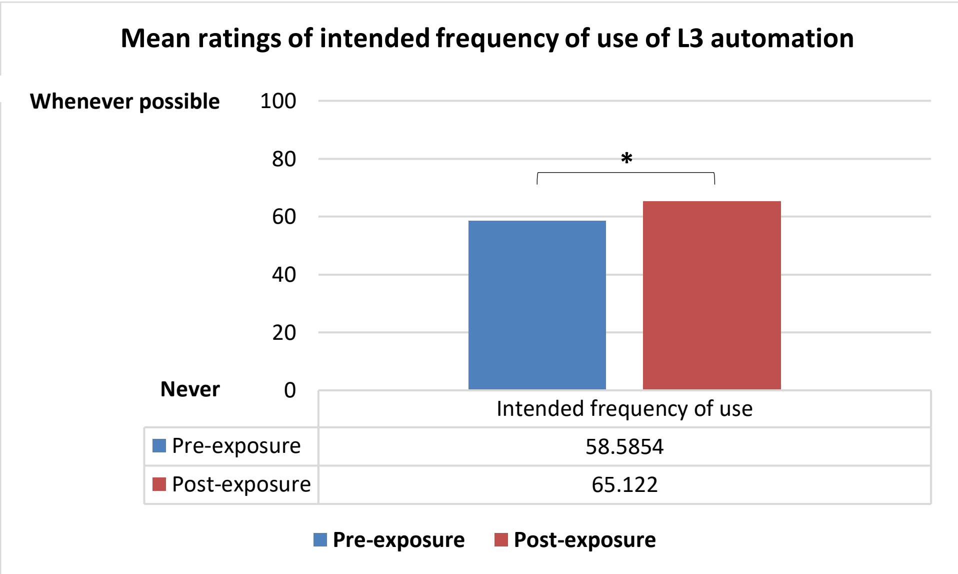


Figure 7.13 *Mean ratings of intended frequency of Level 3 automation use (* p<0.05)*

The effect of exposure to automated driving on participants' intended frequency of use of automation was analysed using the GEE method. The unstructured working correlated matrix, the linear model and the identity link function were selected. In this model, participants were the subject variable and exposure to automated driving (order of questionnaires) was the independent variable. The intended frequency of automation use was the dependent variable.

The GEE test revealed a significant main effect ($\chi^2(1) = 4.271$, $p = .039$) of the exposure to automated driving. These results suggest that as the result of exposure to automated driving in the simulator, participants reported a significant increase in the anticipated frequency of automated driving choices. Parameter estimates are presented in

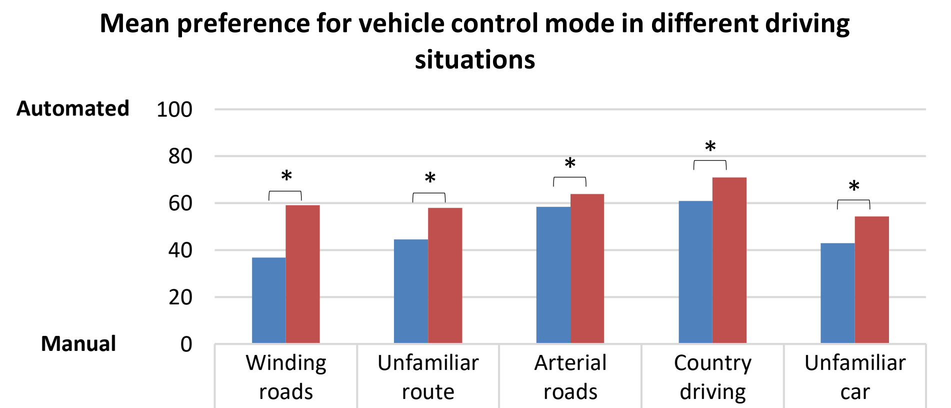
Table 7.13.

Table 7.13 ***Parameter estimates for the intended frequency of automation use***

Parameter	B	SE	95% Wald CI		Hypothesis Test		
			Lower	Upper	Wald χ^2	df	Sig.
Frequency of automation use							
Post-exposure	6.537	3.1629	.337	12.736	4.271	1	.039
Pre-exposure	0	.	.	.	.	.	.

Preference for vehicle control in a variety of driving situations

In each questionnaire, participants were asked to indicate their preference for vehicle control mode by positioning a sliding bar between manual and automated driving for a range of different driving situations. The recorded value ranged between 0 for completely manual preference and 100 for completely automated preference. Mean preferences for five driving situations are presented in **Figure 7.14**.



	Winding roads	Unfamiliar route	Arterial roads	Country driving	Unfamiliar car
Pre-exposure	36.854	44.489	58.415	60.878	42.902
Post-exposure	59.024	58.083	63.927	70.853	54.268

Figure 7.14 *Mean ratings of preference of vehicle control mode in Level 3 automated vehicle in different driving situations (* p<0.05)*

The effects of exposure to automated driving (hypothesis H7.6) were analysed using the GEE method. The unstructured working correlated matrix, the linear model and the identity link function were selected.

Results of the GEE tests identified five driving situations whose ratings were statistically different after experiencing real-time automated driving. These situations were driving in winding roads ($\chi^2(1) = 38.258$, $p < .001$), driving on an unfamiliar route ($\chi^2(1) = 8.377$, $p = .004$), driving on arterial roads ($\chi^2(1) = 5.191$, $p = .023$), driving on country roads ($\chi^2(1) = 9.111$, $p = .003$) and driving an unfamiliar car($\chi^2(1) = 5.745$, $p = .017$). For each of these five situations, there was a statistically significant increase in preference towards automated vehicle control mode. Parameter estimates for these five driving situations are presented in

Table 7.14.

Table 7.14 *Parameter estimates of the effect of exposure to automation on the preference of a driving mode*

Parameter (driving situation)	**B**	**SE**	**95% Wald CI**		**Hypothesis Test**		
			Lower	**Upper**	**Wald χ²**	**df**	**p**
Winding roads							
Post-exposure	22.171	3.584	15.145	29.196	38.258	1	.000
Pre-exposure	0	.	.	.	.	.	.
Unfamiliar route							
Post-exposure	13.585	4.694	4.384	22.785	8.377	1	.004
Pre-exposure	0	.	.	.	.	.	.
Arterial roads							
Post-exposure	5.512	2.420	.770	10.254	5.191	1	.023
Pre-exposure	0	.	.	.	.	.	.
Country driving							
Post-exposure	9.976	3.305	3.498	16.453	9.111	1	.003
Pre-exposure	0	.	.	.	.	.	.
Unfamiliar car							
Post-exposure	11.366	4.742	2.072	20.660	5.745	1	.017
Pre-exposure	0	.	.	.	.	.	.

7.3.3 Effects of driver characteristics and attitudes

Results below report the findings on the effects of demographics categories and attitudes on PAD and PAC. Multiple linear regression was calculated to predict the outcome of dependent variables based on data collected in the Demographics questionnaire. The list of driver characteristics and attitude variables is presented in Chapter 6, Section 6.3.5.For the analysis, all attitude variables (scored on a five-point Linkert scale) were treated as continuous variables. PAD and PAC values were averaged for each participant (across two free-choice drives). A descriptive analysis, correlations and scatter plots of questionnaire variables vs average PAD and PAC were used to examine potential significant relationships before exploration of the model.

PAD (proportion of automated driving) model

A scatterplot of trust in automation vs the ratio of automated driving suggested a possible quadratic component in the relationship between trust in automation and PAD. Therefore, a new variable representing a square value of trust in automation was calculated and added to the model. The minimal model (the simplest regression model with high R^2 and a close adjusted R^2, and normally distributed residuals) consisted of gender, trust in automation and squared trust in automation. The model coefficients are summarised in **Table 7.15**.

Table 7.15 *Coefficients of the minimal PAD model*

Model	**Unstandardized Coefficients**		**Standardized Coefficients**	**t**	**Sig.**	**95% CI for B**	
	B	**SE**	**Beta**			**Lower**	**Upper**
(Constant)	-.861	.596		-1.445	.157	-2.069	.346
Gender	.119	.069	.256	1.732	.092	-.020	.258
Trust	.833	.401	2.530	2.080	.045	.021	1.645
Trust SQ	-.120	.066	-2.212	-1.821	.077	-.253	.014

A significant regression equation was found ($F(3, 37) = 3.357$, $p = .029$) with an R^2 of .214 and adjusted R^2 of .150. Trust in automation ($B = .833$, $t = 2.080$, $p = .045$) was the only significant predictor of PAD. For the same example of a male participant who rated his trust in automation as moderate, the predicted PAD score would be 0.677.

PAC (proportion of automated vehicle control mode choices) model

Multiple linear regression was calculated to predict average PAC based on driver characteristics data collected in the demographic questionnaire (H7.6). For the analysis, all non-binary variables were treated as continuous variables and PAC scores were averaged for each participant (across two free-choice drives). A descriptive analysis, correlations and scatter plots of IVs vs average CAM were used to examine potential significant relationships before the exploration of the model. A significant regression equation was found ($F(3, 37) = 3.538$, $p = .024$) with an R^2 of .223 and adjusted R^2 of .160. Trust in automation ($B = 1.086$, $t = 2.255$, $p = .030$) was the only significant predictor of PAC. Square of trust in automation ($B = -.156$, $t = -2.000$, $p = .053$) was a marginally significant predictor. The model coefficients are summarised in **Table 7.16**. For example, for a male participant who rated his trust in automation as moderate, the predicted PAC score was 0.696. This PAC score suggested that the participant would be likely to choose an automated driving mode for 7 out of 10 events presented in two free-choice experimental drives.

Table 7.16 *Coefficients of the minimal PAC model*

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95% CI for B	
	B	SE	Beta			Lower	Upper
(Constant)	-1.245	.705		-1.766	.086	-2.674	.184
Gender	.141	.081	.254	1.732	.092	-.024	.305
Trust	1.068	.474	2.728	2.255	.030	.108	2.028
Trust SQ	-.156	.078	-2.416	-2.000	.053	-.314	.002

7.3.5 Effect of free-choice vs forced-choice on the selection of vehicle control

The effect of free-choice vs forced-choice on the selection of vehicle control mode (hypothesis H7.9) investigated by matching those decision points from forced-choice drives with compatible instances from free choice drives. Every compatible decision point from the forced-choice drive was matched with the exact location of free-choice drives. In total, seven decision points were compatible with all three drives (two free-choice and one forced-choice). These points were RB, LB, RF1, RF2, Free, VF1 and VF2. The OC1 decision point was matched with only one free-choice drive. **Table 7.17** represents a summary of counts for each compared decision points between free-choice and forced-choice drives.

Table 7.17 *Frequencies of selected driving modes at matching instances of free-choice and forced-choice drives*

Decision point	Free-choice drives		Forced-choice drive	
	Manual	Automated	Manual	Automated
RB	38	43	21	20
LB	32	49	15	26
RF1	28	53	19	22
RF2	37	44	19	22
Free	26	55	14	27
VF1	37	43	20	21
VF2	28	49	17	24
OC1	18	21	15	26

Chi-square tests were conducted for all decision points to evaluate the statistical significance of the difference in proportions of vehicle driving modes observed in free-choice drives vs proportions observed during forced-choice drives. The results of the statistical tests are presented in **Table 7.18**.

__Table 7.18__ The summary of Chi-square tests for each selection point

Selection point	N	Chi-Square	df	p (2-sided)
RB	81	.601	1	.438
LB	81	.298	1	.585
RF1	81	4.515	1	.034
RF2	81	.014	1	.905
Free	81	.151	1	.698
VF1	80	.205	1	.651
VF2	80	.231	1	.631
OC1	39	1.539	1	.215

Chi-Square goodness-of-fit tests indicated there was no significant difference in the proportion of automated vs manual choices between Free-choice drives and Forced-choice drives for the majority of decision points. There was one exception, selection point RF1 (the onset of rain and fog), $\chi^2(1, n = 81) = 4.515$, $p = .034$. The proportion of selected automated vehicle control mode was significantly higher in free-choice drives when compared to forced-choice drives for this decision point.

7.3.6 Summary of results

A summary of all results, including hypotheses and statistical methods used, is presented in **Table 7.19**.

__Table 7.19__ Summary of Study 4 results

H#	Hypothesis	Statistical methods	Results
H7.1	Increase in the level of SC has a negative effect on the selection of automated control mode	Chi-Square tests	Confirmed for all events
H7.2	Increase in the level of the POS has a positive effect on the selection of automated control mode	Chi-Square tests	Confirmed for all events
H7.3	Starting driving in automated mode has a positive effect on PAD	Main-effect GEE model	Only a marginally significant effect observed
H7.4	The exposure to automation increases preference for a higher level of vehicle automation	Main-effect GEE model	Confirmed
H7.5	Exposure to automation has a positive effect on the intention to use automated driving	Main-effect GEE model	Confirmed
H7.6	Exposure to automation has a positive effect on the preference of automated driving in different situations	Main-effect GEE models	Confirmed for driving on winding roads, driving on unfamiliar route, highway driving, country driving and driving in an unfamiliar car
H7.7	Driver characteristics have an effect on PAD	Multiple regression PAD model	Confirmed, trust in automation was a significant positive PAD predictor
H7.8	Driver characteristics have an effect on PAC	Multiple regression PAC model	Confirmed, trust in automation was a significant positive PAC predictor
H7.9	Forcing choice of a driving mode vs free choice of a driving mode does not have an effect on the choice of vehicle control mode.	Chi-Squared tests	There were no statistical differences in results between the two methodologies for the majority of decision points.

7.4 Discussion

This study observed actual driver behaviour in a driving simulator that allowed real-time interaction with Level 3 vehicle automation. In particular, when exposed to a variety of driving situations that resemble everyday, non-critical driving. The majority of hypotheses such as the negative effect of SC (situation complexity), positive effect of POS (perception of safety) and positive effect of trust in automation on the choice of automated driving, and the significant positive effect of exposure to automation on acceptance of automated driving were confirmed. It was concluded that forcing the choice of driving mode does not make a significant difference in comparison with a free-choice of driving mode.

7.4.1 Selection of vehicle control mode during free-choice drives

The results of the analysis of the selection of vehicle control mode during free-choice drives led to several conclusions. The overwhelming preference for manual vehicle control mode in high SC and low POS events suggested that participants might not trust vehicle automation under such conditions. Although no directly comparable study was identified, it was possible to find support for these conclusions in the literature. The link between risk and trust in vehicle automation has been established in previous research. For example, Petersen et al. (2018) evaluated the influence of internal and external risk on trust in vehicle automation and found a negative effect of risk, especially internal, while in a study by Wang et al. (2002), POS was found to be highly correlated to perceived risk.

Reduction in selected automated control mode in high SC and low POS, therefore, suggested that trust in automation played a role in the selection of vehicle control. This finding is consistent with Molnar et al. (2018) who, in a simulator study on the transfer of control, found a significant positive relationship between automated vehicle control mode preferences and the reported trust. Similarly, when exploring data from automated vehicles trials in California, Dixit et al. (2014) found that lack of trust increased the likelihood of a resumption of manual control of the vehicle.

The literature search failed to identify any previous research that investigated the effects of starting vehicle mode in the context of automated driving. Despite the lack of true statistical significance, the overall estimated PAD (proportion of automated driving) was marginally higher for drives that started in automated control mode. This could indicate a possible hysteresis effect (Farrell, 1999) associated with the first change of vehicle control mode in the drive. However, the exploration of this effect was not included in the study design. A more detailed explanation of the hysteresis effect and proposed relevance to the context of choice of vehicle control mode in Level 3 automated vehicle is provided in Appendix G.

It should be noted that, when observing the behaviour of participants at the start of free-choice drives in the course of the experiment, it became evident that some of the participants were not initially aware that they were driving in automated driving mode despite active mode notification being displayed on the virtual dashboard. These participants maintained “ghost” control of the vehicle without noticing that they were not in control. Only when approaching the first event, (either RF or GW) would they become aware, or were made aware by the researcher, that automated vehicle control mode was active. For this reason, PAD values were calculated from the start of the first event, instead of from the start of the drive, until the end of the drive.

7.4.2 Effects of exposure to automation

Following the introduction to vehicle automation, participants were asked to indicate their preferred level of automation on a scale from no automation to full automation, their intended frequency of use of Level 3 automation and preference of vehicle control mode in a variety of driving situations. The same questions were presented after the completion of three experimental drives. The question about the preferred level of automation attempted to answer whether participants would be willing to further delegate the driving task to the higher level of vehicle automation after experiencing automated driving. The result was significant, showing an increase in the likelihood of a higher level of automation being preferred after exposure. Although the majority of participants opted for Level 3 automation as the preferred level in both before-experience and after-experience questionnaires, the biggest difference was a significant drop in preference of driver assistance (Level 2) and an increase in preferences for partial (Level 3) and high automation (Level 4). No participants rejected all forms of vehicle automation or driver assistance, and surprisingly no participants indicated a preference for full automation.

A similar statistically significant effect was observed for the question about the intended use frequency of Level 3 automated driving. These results demonstrated that relatively short exposure to real-time automated driving increased the intended frequency of automation use if the vehicle was equipped with such a system. This observation is supported by Lin et al. (2018) who reported a very positive attitude towards partial automation after short-term exposure to Tesla Autopilot. Similarly, Zoellick et al. (2019) reported participants' acceptance and trust of AVs, perceiving them as safe and declaring intention to use then in the future after experiencing automated driving in on-road test AV.

A significant increase in preference for automated vehicle control mode after exposure to automated driving was identified for five hypothetical driving situations. They were driving on winding roads, driving on an unfamiliar route, driving on arterial roads, country driving and driving an unfamiliar car. It was possible to identify certain patterns that can be applied to these situations. It was speculated that participants did not associate something intrinsically unsafe or complex with these driving situations as no interaction with other road users was suggested in the question. In comparison, mode preference for situations that could be considered unsafe or complex such as any interaction with vulnerable road users (pedestrian crossings, school zones), freeway merging, or driving when sleepy/tired was unchanged or lower after exposure.

However, a certain increase in driving task demands could be associated with driving on winding roads, driving on an unfamiliar route, driving on arterial roads and driving an unfamiliar car. Driving on winding roads requires frequent speed and steering adjustments. Driving on an unfamiliar route requires the driver's additional resources to navigate through new surroundings. Parkes et al. (1991) observed an increase in driver workload when driving in an unfamiliar area during the investigation of the effects of in-vehicle route investigation displays on driver behaviour. Similarly, additional effort might be required if a driver is not very familiar with the car. Driving on arterial roads (highways) is inherently tedious, often over long distances (Noh & An, 2018) and increase driver fatigue (Ting et al., 2008). The idea of automated driving, therefore, likely appeared attractive. Country driving is generally considered more scenic and relaxed. The possible appeal of automated driving in this environment was that the driver was allowed more time to relax and enjoy the environment. It was concluded that, after experiencing automated driving, drivers were able to recognise some of the potential benefits and risks of vehicle automation and apply this new knowledge to hypothetical driving situations. Similar conclusions were made by other researchers. Lin et al. (2018) investigated behavioural adaptation after short-term exposure to Tesla Autopilot and found that drivers learned to identify a relatively safe usage condition and avoid excessive risks. Xu et al. (2018) attempted to explain the influence of direct experience on acceptance of Level 3 AV finding an increase in trust and perceived usefulness.

7.4.3 Effects of driver characteristics on PAD and PAC

The resultant PAD (perception of automated driving) and PAC (perception of automated mode choices0 models were not very strong predictors of driver behaviour in a Level 3 automated vehicle. They did, however, identify trust in automation as a statistically significant predictor. This is an important finding as it confirms the transferability of trust in automation observed in Study 3. In particular for PAC, as the choice of vehicle control mode was the most comparable measure to WTE/WTRC from Study 3 since both dependent variables were observed at identical five scenario events. The absence of driving enjoyment from the multiple regression models for PAD and PAC was a somewhat surprising finding given that it had such a profound effect on the results of Study 3. It was likely that participants were overwhelmed with new experiences such as simulator driving, vehicle automation and interaction with vehicle automation, preventing the manifestation of subjective driving enjoyment attitudes on their choice of vehicle control mode. It is speculated that over time a behavioural adaptation to the automation system would occur as suggested by Wege et al. (2013) and driving enjoyment would become a significant factor in how intensively automation would be used.

7.4.4 Effect of free-choice vs forced-choice on the selection of vehicle control mode

For seven out of eight compared decision points, there were no statistically significant differences in choices of vehicle control mode between two experimental conditions, especially for points located in low-complexity situations. Only one decision point, the RF1 (the onset of rain and fog), produced a significantly different proportion of choices between free and forced drives with the proportion of automated vehicle control mode choices being significantly higher in free-choice drives when compared to forced-choice drives. The RF1 point occurred at the beginning of the RF event, at the onset of deteriorated driving conditions. In forced-choice drives, the simulation would freeze at that moment giving participants time to analyse changes in conditions and decide on the preferred vehicle control mode. In free-choice drives, the vehicle control mode was observed at the same location but as drives were not interrupted, participants had very little time to react to new conditions and resume manual control. Based on the proportions of vehicle control mode choices observed at the RF2 decision point, it was concluded that if enough time was given to participants to analyse dynamic changes in the road situation and react, the proportions of vehicle control mode choices observed at RF1 would be similar under both experimental conditions. For the remaining seven decision points the timing was not as critical as these events were observed when the event was already in a “stable” phase (for example RF2 occurred after drivers were exposed to new conditions for 30 seconds making it very likely that by then they firmly settled on a particular vehicle control mode). In summary, there were no significant differences in outcomes between forced-choice and free-choice of the vehicle control mode.

7.4.5 Participant comments

Participant comments were collected at the end of the Post automation drive questionnaire. Participants were asked to give their reasons for choosing automated or manual vehicle control modes and encouraged to make other comments. The qualitative analysis of reasons for choosing a particular vehicle control mode is presented in Appendix F. Trust has been confirmed as a critical factor for the selection of the vehicle control mode with driver confidence being another critical factor for the selection of vehicle control mode., The importance of driver confidence in the choice of control mode in automated systems was confirmed by several sources such as de Vries et al. (2003), and Lee and Moray (1994).

Some of the participants' comments suggested that their choice of vehicle control mode was influenced by the effort required to switch between control modes. This provided another indication that hysteresis could be a factor in the choice of Level 3 automated vehicle control mode. The suggested hysteresis effect applied to the main research question of this study is presented in Appendix G.

7.4.6 Practical implications of study 4 findings

Similar to Study 3, the results emphasise the importance of appropriate training and education. Drivers need to know all conditions when they can and cannot use Level 3 automated driving. Crump et al. (2016) concluded that despite the obvious benefits of AVs, their effectiveness would be diminished if drivers fail to understand how to use automation correctly. Although it has been shown that the exposure to automation was very effective in correcting driver behaviour as suggested by Feldhütter et al. (2016), the correct initial training would be more important before exposure to automation on real roads than in a driving simulator. Training in a driving simulator before the first real road deployment, would, therefore, accelerate learning and increase road safety as it could provide exposure to critical events such as take over requests in a safe environment.

The study also confirmed that building trust in vehicle automation will be a major factor in the acceptance of automated vehicles. Petersen et al. (2018) in their study on situational awareness and driver's trust in automated driving systems, concluded that because of the lack of trust drivers were failing to take full advantage of the automated vehicle.

The strong effects of SC (situation complexity) and POS, on the choice of vehicle control mode, demonstrated that perceived SC and POS were important factors in the acceptance of automated driving. Therefore, the successful adoption of automated driving could be mitigated by the simplification of road infrastructure, or at least by representing a lower SC to the driver. This suggests that the adaptation of existing road infrastructure in anticipation of vehicle automation should precede the legalisation of automated driving. A similar idea was discussed by Oliver et al. (2018) who suggested that the readiness of road infrastructure was the key step in safe accommodation of automated vehicles, more important than the readiness of vehicle technology. Complex urban environments, temporary work zones and reduced visibility due to bad weather conditions are the main challenges (Nitsche et al., 2014).

7.4.7 Recommendations for future research

For future research of automated driving in a driving simulator, it is recommended that the user interface for switching between driving modes also allows a resumption of control via multiple actions, similar to the deactivation of cruise control in cars. Using a higher-fidelity simulator would allow observation of the effects of different driving speeds. The importance of driving enjoyment could be further explored after the relevant experience with vehicle automation is gained. The effect of situation complexity on WTE and choice of vehicle control mode in Level 3 AV, should be confirmed in naturalistic studies when public use of such vehicles become legalised.

During data analysis, especially qualitative analysis of participant comments, several participants were identified as being less confident drivers. Their comments suggested a choice to delegate vehicle control to automation in more complex situations. Therefore, a study that would profile participants by their confidence in driving skills would be able to answer more questions about the effect of confidence in automated driving especially in combination with trust in automation. At the end of the experimental session, several participants commented that they did not want to make a change of vehicle control mode during experimental drives, preferring to stay in the already active mode instead. A similar observation is reported by Lee and Moray (1994) who identified inertia in the reliance on automation, observing that the current use of automation depended on the previous use, due to complexities involved in the change of the control mode. This behaviour is likely to be linked to the effect of hysteresis (Farrell, 1999) on WTE. It is therefore recommended that this construct be included in the JCTF and further investigated in the context of Level 3 automated driving.

7.4.7 Study limitations

This study attempted to present automated driving as close as possible to real-world conditions. However, as the study was conducted in the simulator, participants did not experience actual risk and therefore results could be different from those obtained in real-world conditions. Similar observations were made by Walch et al. (2016) and Jamson et al. (2013). Feldhütter et al. (2016) concluded that the experience of automation in a driving simulator cannot be indiscriminately transferred to the real-world and findings need to be verified under real road conditions. Therefore, it is conceivable that some reactions would differ in real-world driving. However, no critical events were part of the scenario and for most of the driving, it could be argued that the difference between simulated and real-world driving did not affect results significantly as confirmed by the findings of Study 1.

The potential confounding effects of the presented automated driving style on acceptance of AV, identified in Study 3 remain. It was beyond the scope of this study to attempt customisation of the automated driving style as suggested by Li et al. (2017) and Siebert et al. (2017).

Some of the participants possibly did not entirely understand the experimental task. They were asked to select the driving mode they felt the most comfortable with, at any time. Some participants completed drives without changing driving mode, while some participants were changing driving mode too frequently (as if it was expected of them to switch between two vehicle control modes). It was speculated that longer or repeated exposure would reduce or eliminate frequent switching between driving modes as participants would learn when to use and adapt their behaviour to the automation system.

Although the interface for changing driving mode generally functioned satisfactorily under experimental conditions as participants were not presented with a secondary task, lack of steering wheel movement and inability to disengage automated control mode via steering wheel or brakes might have had a certain negative effect on willingness to change driving mode. For example, participants, at least initially, had to look for the automation button and take a view of the road. This problem would almost certainly be eliminated by the implementation of steering wheel movement during automated driving and additional disengagement options such as automated steering wheel override or application of brakes.

There were certain limitations associated with the qualitative analysis of participants' comments. The research is conducted in a driving simulator. Although the best effort was made to represent realistic driving in AV it is likely that the experience on real roads would be somewhat different and may result in somewhat different comments.

7.4.8 Conclusions

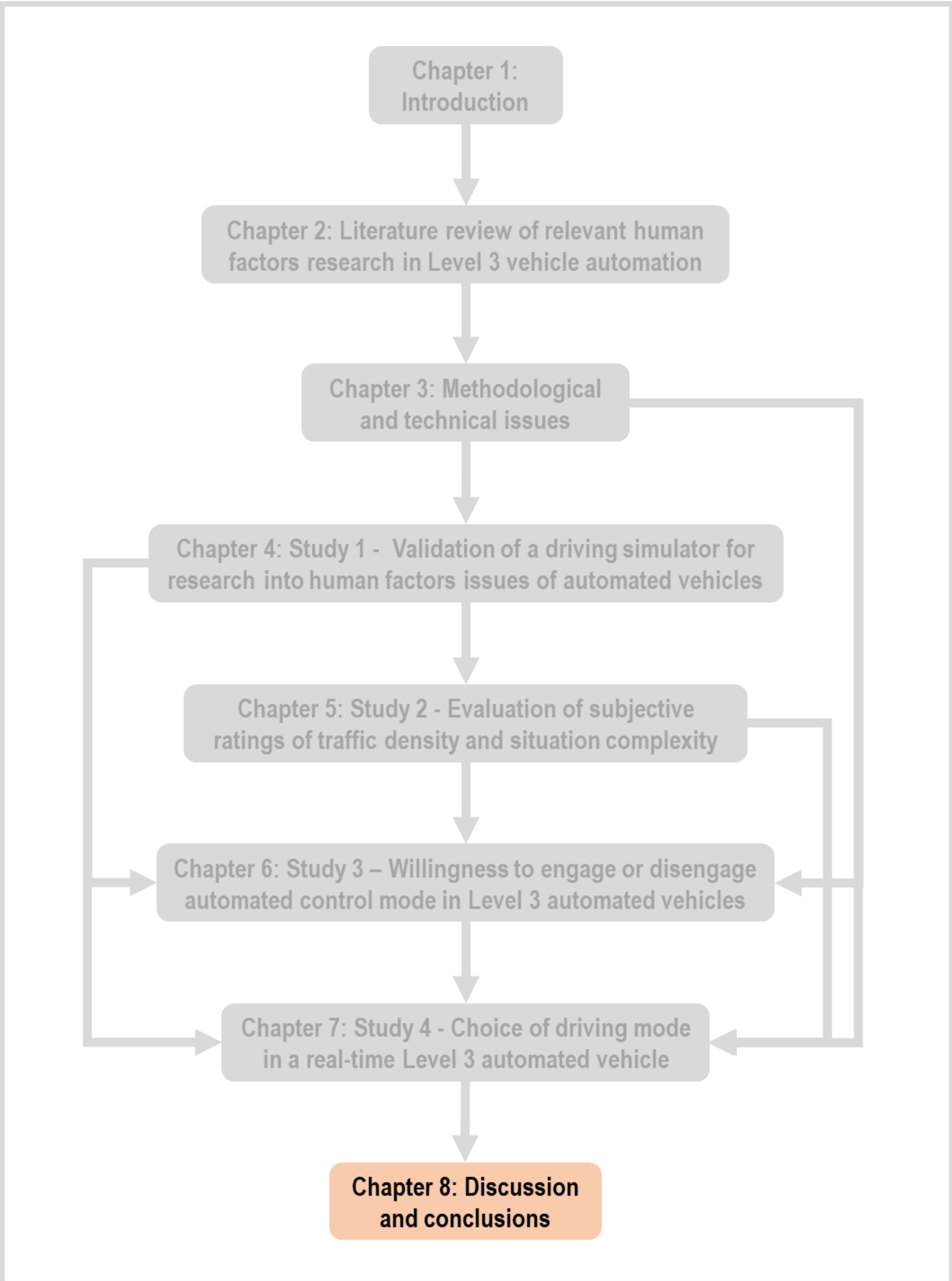
There were three major findings of this simulator study. The first finding was the confirmation of WTE as a strong predictor of the actual choice of vehicle control mode when observed during a specific driving situation in a Level 3 automated vehicle. The second finding was a strong effect of short-term exposure to vehicle automation on the preferred level of vehicle automation and intended frequency of use of Level 3 automated driving. The third finding was the identification of trust in automation as an important predictor of the choice of vehicle control mode.

The strong effects of SC and POS on the choice of vehicle control mode in a simulated Level 3 automated vehicle demonstrated that participants increased their engagement in automated driving in events that were less complex and perceived as safer, suggesting that driver trust of AV in more complex driving situations will need to be improved for successful uptake. The same effect was observed on the measure of WTE in Study 3. Since Study 3 and Study 4 were based on the same scenario events, WTE could be used as a predictor of the actual choice of vehicle control mode in a specific driving situation.

The effects of exposure to automation were significant, generally reporting a positive experience. After experiencing automated driving, participants demonstrated a better understanding of the capabilities and limitations of Level 3 automated driving and were more positive regarding the acceptance of higher levels of automation. The study also confirmed that the presented level of automated driving was acceptable to the majority of participants. This was reinforced by the observation that some participants did not realise that the experimental drive started in automated driving mode and proceeded with manual ("ghost") driving. They did not realise that the car was not under their control suggesting that they were content with automated vehicle control system performance.

Trust in automation was consistently identified as the positive predictor for the selection of automated vehicle control mode in Level 3 automated vehicle. The greater trust in automation observed in participant attitudes was reflected in greater use of vehicle automation in experimental drives. This finding was supported by qualitative analysis of participants' comments where they singled out trust as the key reason for deciding to engage automated control mode.

CHAPTER 8



Chapter 1: Introduction
Chapter 2: Literature review of relevant human factors research in Level 3 vehicle automation
Chapter 3: Methodological and technical issues
Chapter 4: Study 1 - Validation of a driving simulator for research into human factors issues of automated vehicles
Chapter 5: Study 2 - Evaluation of subjective ratings of traffic density and situation complexity
Chapter 6: Study 3 – Willingness to engage or disengage automated control mode in Level 3 automated vehicles
Chapter 7: Study 4 - Choice of driving mode in a real-time Level 3 automated vehicle
Chapter 8: Discussion and conclusions

Chapter 8 General Discussion and Conclusions

The overall aims of this research program were to identify and evaluate the factors that influence WTE in Level 3 automated vehicles under everyday driving situations. This research assumed that, in the foreseeable future, all new vehicles would have Level 3 automation capability, Therefore, all drivers of new vehicles may be able to freely choose to engage and disengage vehicle automation as desired. Four experiments were undertaken during the research program: one combined simulator and on-road, one was laboratory-based and two involved driving simulation experiments. This chapter summarises all major findings of the research and discusses the key results with reference to previously published work, highlights theoretical and practical implications, and finally identifies limitations of this research with recommendations for future research.

8.1 Chapter summary

The research contained in this thesis is presented in eight chapters. Chapter 1 introduced the research topic in a form of a problem statement and vehicle automation as a potential solution. Levels of automation were presented as well as a summary of the benefits and concerns associated with this technology. The main human factors issues associated with automated driving were introduced and discussed. Overall research aims and questions were formulated. At the end of the chapter, the scope of the research and the structure of the thesis were defined.

Chapter 2 contained a review of the current literature, highlighting an increase of interest in research of vehicle automation as the launch of automated vehicles approaches. While automated vehicles are still not freely available, a brief review of research methodologies was presented to aid the resolution of methodological issues. From past research, a suitable theoretical framework (JCTF) was selected and applied to the research questions within the defined scope of the research, resulting in the identification of factors that were likely to influence a driver’s willingness to engage in automated driving or resume manual vehicle control. An in-depth review of each of these factors led to the formulation of the main hypotheses that were tested in experimental studies.

Chapter 3 links the work done on a range of technical and methodological problems that needed to be resolved to facilitate simulation research during this research project. They include steps in resolving the representation of automated driving for the simulator validation study and issues in the development of real-time automated driving capabilities of the driving simulator. Methodological options for the validation study were evaluated and determined. Representation of the motion base was evaluated with a small pilot study and finally, implementation of real-time automated driving was described. Real-time driving in the simulator required the development of control algorithms for automated driving, the development of a basic functional physical HMI as well as the choice of an automated driving style. Several conclusions were made in the course of this process. The development of the practical automated driving style indirectly confirmed the importance of this issue and the complexity of the problem manufacturers will be facing. The evaluation of the perception of motion base proved that, in this context, a motion base can be substituted with cheaper tactile transducers.

Chapter 4 described Study 1, which set out to validate the use of the driving simulator for research into human factors issues with automated vehicles. In this study, driving behaviour observed in terms of subjective WTE (and WTRC) and subjective POS was compared between similar situations encountered during on-road and simulator drives. Ratings of similar situations between two experimental conditions were analysed. As there was no significant difference observed between on-road and simulated driving the validity of the driving simulator was confirmed for use in further experimentation. Furthermore, analysis of data resulted in the development of a set of guidelines for the design of simulator-based scenarios for research of human factors in automated driving. These include the characteristics of events and conditions that are well represented in the simulator. Understanding how different levels of traffic density and situation complexity are perceived among different participants emerged as an important issue explored in Study 2.

Chapter 5 outlined Study 2, which explored subjective perceptions of levels of traffic density and situation complexity during different driving situations. This study aimed to assess the extent of variability of subjective judgements in these two categories as well as to establish a relative scale of situation complexity to be used in subsequent simulator studies. The results of data analysis revealed low levels of agreement among participants, especially for situation complexity. These findings led towards the formulation of several guidelines for the design of simulator scenario events to mitigate potential confounding effects of variability in perceived levels of situation complexity and traffic density. For example, only two distinctive levels of traffic density and situation complexity, low and high, should be used in the design of simulator scenarios. These guidelines were used in the design of studies 3 and 4.

Chapter 6 reported the findings from Study 3, which investigated the effects of variable driving conditions in a simulated Level 3 automated vehicle on WTE (willingness to engage automation), WTRC (willingness to resume control) and POS (perception of safety). The manipulated conditions were situation complexity, vehicle control mode and driving speed. Participants were asked to rate their WTE during manual drives and WTRC automated drives, as well as POS for each scenario event. The results revealed a strong effect of situation complexity on both WTE and POS. Overall, participants of this simulator study were more willing to engage automated driving and reported a higher perception of safety in less complex situations while high-speed conditions had a positive effect on WTRC. Investigation of driver characteristics identified trust in automation, driving enjoyment and kilometres travelled per week as significant predictors of WTE, while significant predictors of WTRC were the trust in automation, driving enjoyment and type of transmission in the participant's car.

Chapter 7, the final study of this research program, documented the findings from Study 4, which investigated the relationship between WTE/WTRC and drivers' actual choice of vehicle control mode. This study observed driver behaviour in an interactive Level 3 simulated vehicle. Participants were able to alter between manual and automated vehicle control modes during simulator drives. Experimental drives contained the same events used in Study 3 where the choice of driving mode was observed. Data analysis revealed that a more complex driving situation resulted in a reduced selection of automated driving mode while a higher perception of safety increased selection of automated control mode. Investigation of driver characteristics identified the level of trust in automation as a significant predictor of choice of vehicle control mode. These findings provided evidence of transferability of subjective WTE to the choice of vehicle control mode in a real-time Level 3 simulated automated vehicle. A strong positive effect of exposure to automated driving on perceptions and intended use of vehicle automation was observed. Qualitative data analysis of participant comments confirmed, at a strategic level, trust as one of the key factors for the choice of vehicle control mode and identified driver confidence as another important factor.

8.2 Integration of the findings with previous research

Before this research, no peer-reviewed publications had explicitly investigated drivers' willingness to engage automation, a new behavioural phenomenon that became meaningful in Level 3 AVs. Also, only a small number of unrelated papers touched on non-critical driving in the context of vehicle automation (Bellem et al., 2016; Jamson et al., 2013; Neubauer et al., 2012).

In the current research, WTE was confirmed as a reliable predictor of choice of vehicle control mode in Level 3 AV (automated vehicle). The program's results demonstrated that, when facing more complex everyday driving situations, drivers indicate a preference to control the vehicle manually, rather than engage automation. When the driving situation was perceived as less safe, for example entering unsignalised intersection with other vehicles being involved, participants preferred to control the vehicle themselves, rather than delegate the driving task to automation. This means that drivers of Level 3 AV fundamentally trusted themselves more than the automated system. Another very important finding was the strong association between WTE/WTRC and POS.

However, there are several important caveats to consider. First, these results were obtained after only a single session in the driving simulator. Most of the participants experienced Level 3 automated driving for the first time during this session. In addition, only a few participants experienced some forms of driving with new technologies such as ACC (adaptive cruise control) and LKA (lane keeping assist). Therefore, it is not surprising that when facing the novelty of automated driving, they preferred the familiarity of being in control of the vehicle. A similar conclusion was made by Lee and Moray (1994) who observed a bias towards manual control during initial interactions with the system. As the participants' attitudes changed after such a short exposure to automated driving, it is very likely that their behaviour in terms of WTE and choice of vehicle control mode changed as well. The findings of this study therefore can be applied to issues that users will face when Level 3 automated vehicles are initially deployed.

Results suggest that they will need to be convinced that AVs are safe by developing trust in automation. Trust in automation was found to be a significant predictor of both WTE and choice of vehicle control mode. This finding was supported by an analysis of participant comments after experiencing automated driving in the simulator. There was overwhelming support for this finding in the literature (Mirnig et al., 2018). Trust is also identified as a dynamic process that changes over time due to a better understanding of vehicle automation operational domain, capabilities and limitations (Beggiato & Krems, 2013; Lee & See, 2004).

Driver confidence (self-confidence) was identified as a negative predictor of the choice of automated driving mode and, therefore, it is likely to be a negative predictor of WTE at the strategic level. This finding is supported by Noy et al. (2018) who concluded that confident and highly skilled drivers are less likely to use automated systems. The difference between trust and confidence was identified as a potentially key motivational factor for the selection of vehicle control mode. Similarly, De Vries et al. (2003) concluded that the difference between trust and self-confidence is highly predictive of the selection of the automated mode in route planning. Strong support for this finding is provided by Lee and Moray (1994) who, although conducting a study in a more general context of automation, identified trust and self-confidence as two factors that guide the operator's control mode allocation strategy in interactions with automation.

The qualitative analysis from Study 4 was able to identify only a small number of participants that declared low self-confidence and therefore based their choice on trusting automation in complex situations. In reality, drivers like these are rare; thus, the net effect is also likely to be very small. However, the introduction of vehicle automation is expected to contribute to the loss of driving skill and increase the proportion of drivers with lower self-confidence, increasing the implications of this factor.

Driving enjoyment was found to be a significant negative predictor of WTE and a significant positive predictor of WTRC. This is directly supported by Hooft Van Huysduynen et al. (2018) who found enjoyment of manual driving to be one of the main reasons for disabling automated driving. Hegner et al. (2019) too found that the negative influence of driving enjoyment on an intention to adopt AVs. Interestingly, though, these findings were not confirmed in Study 4. It is speculated that the novel experience of real-time automated driving in Level 3 AV suppressed possible effects of driving enjoyment.

None of the observed driver characteristics (age, driving experience and gender) was a significant predictor of WTE or choice of vehicle control mode, possibly due to a fairly homogenous sample used in this research. The original hypotheses on these categories were based mainly on research conducted via surveys whereas this research was based on driving simulator experiments during which participants were able to learn more about and experience vehicle automation. There are examples in the literature showing the diversity of findings suggesting that the effects of driver characteristics not be very strong in comparison with other factors investigated in this research.

Reconsideration of the theoretical framework

In relation to the adaptation of JCTF (Joint Conceptual Theoretic Framework) used to guide this research, previously noted complex interactions between constructs (Sullivan et al., 2016; Zoellick et al., 2019b) have been well confirmed through numerous examples in the literature. For example interactions between risk, control and trust in automation (Lee & Kolodge, 2018; Liu, Ma, et al., 2019); trust in automation and exposure, the experience of failures and malfunctions (Kraus et al., 2020); driver characteristics and exposure to automation (Crump et al., 2016; Gold et al., 2015) and many more.

This research attempted to explain some of these interactions broadly outlined by Wege et al (2013) in their Joint Conceptual Theoretical Framework (JCTF), using the results obtained from the experimental studies conducted in this thesis. These findings are incorporated in a revised adaptation of the JCTF for WTE, presented in **Error! Reference source not found.**. Factors that were confirmed to have an overall positive effect on WTE are presented in green font, while factors that had an overall negative effect on WTE are presented in red font.

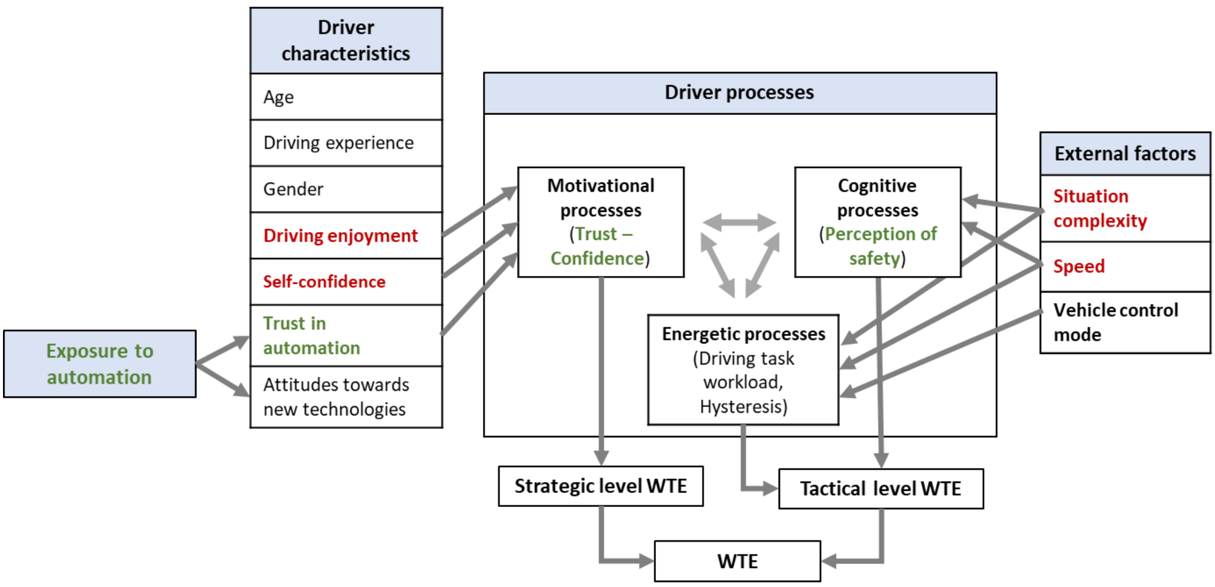


Figure 8.1 *Revised adaptation of the JCTF for WTE*

This diagram includes factors that were observed during the experimental studies and allowed the identification of more specific correlations between relevant constructs, therefore addressing one of the deficiencies of the original theoretical framework. These correlations were represented as links between factors and the target driver process. The resultant WTE was presented as a sum of strategic level WTE and tactical level WTE. The perception of safety was re-classified as a cognitive process as it was measured for each question point during experimental drives. Based on the observation of driver behaviour in a simulated real-time AV, two additional constructs to the existing theoretical framework were proposed: exposure to vehicle automation and hysteresis due to driver responses being dependent on the current state of automation (Farrell, 1999).

The addition of exposure to automation was considered very important since it had a strong effect on increasing trust in automation and intention to use automation. It addressed dynamic changes in driver motivational processes and attitudes over time.

Although not explicitly investigated in this research project the hysteresis was identified as a possibly significant factor for the selection of control mode in Level 3 automated vehicle. It was classified as an energetic process since it addresses the effort required for making a change of the vehicle control mode.

8.3 Contributions to knowledge and practical implications

8.3.1 Contributions to knowledge

This research program investigated aspects of driver behaviour in Level 3 automated vehicles in non-critical situations. For many years the main research focus here was on critical situations such as the transition of control due to automation failure. However, non-critical driving represents a vast majority of driving experience and deals with a very broad range of human factors issues. Although it was not possible to explore all of these issues within this thesis, several important theoretical and methodological contributions were made.

Theoretical contributions

At a tactical level, a strong negative effect of situation complexity on WTE was identified, as well as a strong association between POS and WTE. This means that if drivers of Level 3 automated vehicles perceive that a driving situation is complex, they would be less willing to use vehicle automation since they feel safer when manually controlling the vehicle. If drivers' perceived level of complexity is reduced, they are likely to be more willing to engage automated driving. Since better-trained drivers are more capable to deal with more complex situations (Cegarra & van Wezel, 2012), driver training is one way to reduce perceived situation complexity by developing automatic information processing (Paxion et al., 2014a), resulting in driving situations being seen as more transparent and predictable. Therefore, improving driver's cognitive and perceptual skills will help increase the engagement of vehicle automation.

On a strategic level, trust in automation was identified as a significant positive predictor of WTE, driving enjoyment was identified as a significant negative predictor of WTE, and exposure to automated driving had a strong positive effect on the intention to use automation. Therefore, increasing trust in automation will increase drivers' willingness to engage automation, particularly under more complex driving situation where it was found that drivers indicated a reduced willingness to use automation. Apart from positive exposure to automation, trust in automation can be increased with training, education, publicity, advertising and evidence of automation safety (Kalra & Groves, 2017). Since drivers who derive personal enjoyment from driving were shown to be less willing to engage automation, they should be made aware of the benefits of automated driving and encouraged to appreciate these, at least in certain situations where risks may be increased, such as when driver fatigue may be present. Driver confidence (self-confidence) was identified as a negative predictor of the choice of automated vehicle control mode. Self-confidence was likely a representation of internal locus of control leading to a preference for manual vehicle control and could be addressed with training and increased awareness of the benefits of automation. These findings provide stakeholders with theoretical tools for controlling the path towards the safe and successful introduction of Level 3 vehicle automation.

The research here also made significant contributions to the theoretical framework outlined by Wege and colleagues in 2013 in their Joint Conceptual Theoretical Framework (JCTF). Firstly, it further developed the theoretical framework for the investigation of WTE by identifying factors (such as situation complexity) relevant to non-critical driving in Level 3 AVs. The resultant version of the theoretical framework was updated to reflect the effect of each factor on WTE as well as interactions with other constructs. Also, new constructs, hysteresis and exposure to automation, were added to further expand the original framework.

Methodological contributions

This research further outlined several methodological contributions to the area of driver performance in automated driving. Firstly, the driving simulator was shown to be a useful research tool for the investigation of human factors issues in Level 3 AVs. The validation process was documented and since it was probably the first such study, it may provide useful information that can be applied to future validation studies. In particular, how to present automated driving safely and effectively in the absence of real AV, how to optimally design experimental scenarios and how to deal with limitations of driving simulator fidelity such as restricted field of view and lack of motion base.

Furthermore, the exploratory research leading to the main simulator experiments resulted in the formulation of guidelines that can be used for the design of experimental simulator drives. These guidelines identify driving situations that are suitable for investigating in the simulator, situations that do not transfer well and provide advice on the implementation of independent variables in scenarios. For example, high-risk situations do not transfer well in the simulator.

Issues encountered during the development of simulator scenarios for the two main simulator studies and all solutions were documented in a dedicated chapter and provide useful information to researchers in a similar position. In particular, the design of HMI for simulated AV and practical implementation of automated driving style in the simulator contains several practical suggestions that may contribute to resolving these problems. For example, automated driving style should incorporate individual preferences without compromising safety.

Ultimately, the findings of this research could help the safe adoption of automated driving, as well-designed automated vehicles have the potential to eliminate a major cause of road accidents.

8.3.2 Practical implications for stakeholders

It is widely accepted that the benefits of vehicle automation will ultimately outweigh any potential problems associated with its introduction (Young et al., 2016). Hence, activities that facilitate the adoption of safe automated driving should be supported by all stakeholders (users, policymakers, governments, car manufacturers, insurance companies, driving schools and media). A coordinated effort from all stakeholders is required if the introduction of AVs is going to be successful in every aspect. This section suggests several practical implications that are based on the findings of this research.

Manipulation of perceived situation complexity

The identification of situation complexity as a significant factor in automated driving vehicle control mode choice was one of the major findings of this research. As perceived situation complexity was found to have such a strong effect on WTE and choice of vehicle control mode, manipulation of this perception could be utilised to influence the choice of how and when vehicle automation is used by drivers. Simplification of complex driving situations or a reduction in perceived complexity could increase WTE, and, therefore, facilitate exposure to automated driving. This can be applied to roads, traffic regulation systems, other infrastructure and AV HMI. For example, Birrell and Young (2011) demonstrated the ability of HMI design to influence driver behaviour.

Endsley (2017) also provided guidelines for reducing the complexity of the automated system. Advanced technologies such as augmented reality could be utilised (Pijnenburg, 2017). Thus, visibility in fog could be enhanced by superimposing a 3D model of a driving scene created from outputs of sensors that are not affected by these conditions (Bijelic et al., 2020), using a head-up (HUD) display. Similar and much more complex systems are already implemented in later generations of jet fighters such as the F-35 (Rockwell Collins, 2014), therefore, it is just a matter of time before they become used in civilian applications.

Conversely, the presentation of increased complexity is highly likely to have the opposite effect. One practical application of an increase in perceived complexity could be its application in providing a subtle mechanism to keep the driver “in the loop”. Hence, active manipulation of perceived SC has the potential to influence the choice of vehicle control mode and achieve optimal safety benefits.

Exposure to automation and development of trust

This research found that limited exposure to automated driving in the simulator had a significant effect on changes in participant attitudes towards vehicle automation. A positive exposure to automated driving, even short exposure, is likely to reinforce and accelerate the adoption and acceptance of AVs. As driver trust in automation is quickly developed by exposure, there should be opportunities to experience truly automated driving using driving simulators, similar to the long-running practice of demonstration of Tesla Autopilot (Level 2) offered to potential buyers. This will most likely be followed by other car manufacturers. Driving schools could be another avenue for providing a more systematic exposure to AVs. Governments too could stimulate accessibility of AVs as well as insurance companies with reduced premiums.

Altering driver enjoyment

Driving enjoyment was identified as a significant predictor of driver’s willingness to engage or disengage vehicle automation. This finding offers another tool that could potentially influence the adoption of automated driving. Once Level 3 vehicle automation issues, such as transfer of control, are resolved and the safety benefits confirmed, the perception of driving enjoyment should be altered. That means shifting emphasis via education or advertising, from enjoying being in control of the vehicle to the enjoyment of the comfort, safety and other benefits offered by vehicle automation such as the ability to use travel time for work or leisure.

Management of driver’s expectations and AV certification

In the course of this research, trust in automation was consistently found to be the most significant predictor of driver’s willingness to engage automated control mode, therefore, making Level 3 automated vehicles particularly vulnerable to overtrust. Since there is no effective way of designing ADAS to prevent overtrust in the system (Ekman et al., 2019), driver training and education need to focus on understanding what AVs can and cannot do, therefore ensuring appropriate use and developing trust in automation and development of an accurate mental model of AVs capabilities and limitations. The reinforcement of an accurate mental model could be aided by introducing more accurate, possibly conservative, naming of technologies employed in vehicle regulating policy. Until human intervention is no longer required during automation, as is the case with Level 3, terms “automation” and “automated vehicle” should be avoided and substituted with a fundamentally more correct naming such as “advanced driver assistance” and ADAV (advanced driver assistance vehicles). This could increase the awareness of the driver’s role as the supervisor of the automated system and emphasise the importance of staying in the loop since the name of a system impacts the driver’s expectations (Abraham et al., 2017). It may also aid in resolving legal issues of responsibility in the case of accidents and therefore accelerate the deployment of Level 3 AVs. Car manufacturers would almost certainly be motivated to advertise their cars as AVs as soon as possible. Therefore, some form of certification could be required before vehicles are allowed to be called “automated”.

Standardisation of human-machine interface and driving algorithms

Work on resolving methodological and technical issues for this research identified the lack of a standard HMI interface for automated driving and potential issues stemming from the presented automated driving style. Therefore, HMI (human-machine interface) in automated vehicles, at least at a fundamental level, should be better standardised across all vehicles as facing an unfamiliar interface could be a safety risk, particularly if not optimally designed. Similarly, automation control algorithms that also determine vehicle driving style should be standardised, transparent and predictable. HMI Standardisation is especially important for interactions with vulnerable road users and critical (ethical) decision making in complex road environments.

Taken together, it is anticipated that these interventions could serve as a catalyst for the successful and safe introduction and uptake of Level 3 vehicle automation.

8.4 Limitations of the thesis and recommendations for future research

The findings from this research program should be interpreted in light of several limitations.

Lack of real AVs and standards for HMI and driving style

The most transparent limitation is related to the lack of real and legal automated vehicles used in the research program. Hence, the research conducted was constrained to driving in a simulated environment and the validation of the driving simulator was conducted with participants being placed in the front passenger seat of both the on-road car and simulator, with participants being asked to assume that they were the driver of a Level 3 AV and able to resume manual control at any time. While the simulator used was validated against equivalent on-road driving scenarios, simulated driving is, nevertheless, always subject to replicated driving conditions, lack of real risks and consequences and a degree of “entertainment”. It would be useful to use on-road driving as well as a simulation in future research in this area. Therefore, it is important to understand the effect of limited simulator fidelity. Guidelines for the design of simulator experiments based on the results of the validation study and Study 2 may help to minimise the effects of such limitations.

Another issue stemming from the lack of on-road AVs was the lack of any standard for the design of a human-machine interface, necessitating the development of a version here that may differ from future implementations in real vehicles. The same applies to the automated mode driving style developed for this research. These issues could have an effect on driver behaviour in automated vehicles and therefore influence WTE.

A number of assumptions had to be made in this research, given the novelty and uniqueness of the experimental program and the lack of definitive published research data. As noted above, on-road studies are necessary to provide empirical evidence for many research questions investigated in this research. In particular, research is required to investigate both HMI design and automated driving style. The design of the HMI is likely to influence how the transition of control resulting from automation fallbacks is handled by the driver while automated driving style needs to find a compromise between internal (driver) and external (other road users) acceptance.

As the moment of practical deployment of Level 3 AVs is approaching, there will be more opportunities for conducting research under increasingly more realistic conditions, therefore increasing the overall face validity of results. This development will create an opportunity for exploration of the effects of various HMI designs as well as different automation driving styles. Adding these pieces of information together will provide a solid foundation for developing an accurate model of WTE in Level 3 AV.

Limited exposure to interactive automated driving

As stated previously, due to simulator software limitations participants were not able to interact with vehicle automation until the last study. Although experimental tasks in studies 1 and 3 did not require interaction with an automated system participants were denied an interactive automated driving experience where they were able to change control mode and this could have influenced their perception of automated driving. Even when they were able to change control mode in Study 4 the total exposure time was limited. Therefore, the effects of exposure should not be overgeneralised.

Limited number of factors and interactions were investigated

By their very nature, PhD research programs are limited in their scope of issues that can be addressed given the time constraints. Initially, it was hoped that the PhD work might be able to investigate more factors that determine WTE in Level 3 automated driving and produce a theoretical model of WTE. However, the literature review revealed that the range of potential contributing factors to WTE was very broad.

Moreover, it was further limited by the realisation that many of the factors being investigated are complexly interrelated. These findings, in conjunction with the ongoing evolution of automated driving and lack of design standards and legislation, suggested that any practical theoretical model of WTE would most likely be incomplete. Also, due to the above reasons and other practical limitations, such as budget and time, the scope of research could not address all possible factors associated with WTE or choice of vehicle control mode in Level 3 AV. However, it has been anticipated that all main factors relevant to research questions were addressed in some form.

Many of the factors identified in the adaptation of the JCTF that were not addressed in this thesis, can be explored in the investigation of WTE. For example, the effects of trip characteristics, different mental models, HMI designs, automated driving styles, rate of failures and malfunctions, locus of control and driver confidence, and the new construct, hysteresis on changes of the vehicle control mode. In particular, driver confidence may have a major impact on WTE and the acceptance of Level 3 AVs. These and all other factors that constitute the original theoretical framework should be addressed when practical constraints inherent to the simulator and availability of automated vehicles are resolved.

It was accepted that there were interactions between factors, however, due to the inherent complexities in the exploration of these interactions, factors were examined separately and largely in isolation. Future research experiments could be designed to specifically investigate the interactions between different constructs to facilitate construction of behavioural models. The effects of driver characteristics such as age, driving experience and gender could be targeted during the recruitment process. Effects of exposure to automated driving need to be addressed in a repeated measures study, ideally as a naturalistic study in a road-legal Level 3 AV.

The findings from the literature suggest that trust in automation is likely to increase, drivers are likely to lose some of the driving skills and become complacent. In that context, the importance of other factors such as driving enjoyment and motion sickness is likely to increase and should be evaluated. Finally, the effects of exposure to automation such as behavioural changes should be observed through every stage of vehicle automation evolution.

8.5 Conclusions

This research was conducted at a pivotal stage in automotive history as the number of vehicles equipped with Advanced Driver Assistance Systems is growing and such systems are becoming more capable of replacing the human driver. Once the floodgates to conditional automated driving are open, drivers of Level 3 automated vehicles will have a choice of vehicle control mode. The success of vehicle automation will depend largely on whether this technology meets the needs and expectations of users.

This research program set out to address the shortfall in peer-reviewed research on WTE (driver's willingness to engage in automated driving). As a suitable test vehicle was unavailable, MUARC's newly-built simulator for automated driving was validated and shown to be a fitting test environment. Several factors were shown to be important in assessing WTE and the actual choice of vehicle control mode in a Level 3 automated vehicle. The complexity of the driving situation, perception of safety and trust in automation were particular issues for the drivers tested here in choosing when to give control to the vehicle and when to resume manual driving.

The overall conclusions are illustrated in **Figure 8.2**: these show the factors that were found to contribute to increased drivers' willingness to engage vehicle automation and their choice of automated vehicle control mode. They are divided into two groups, strategic and tactical, and they all contribute to increased WTE directly or indirectly by increasing trust in automation. For example, increased POS directly increases driver's WTE and chances of choosing automated vehicle control mode. POS can be increased if a driving situation is perceived as less complex which can be achieved by improving the driver's cognitive and perceptual skills.

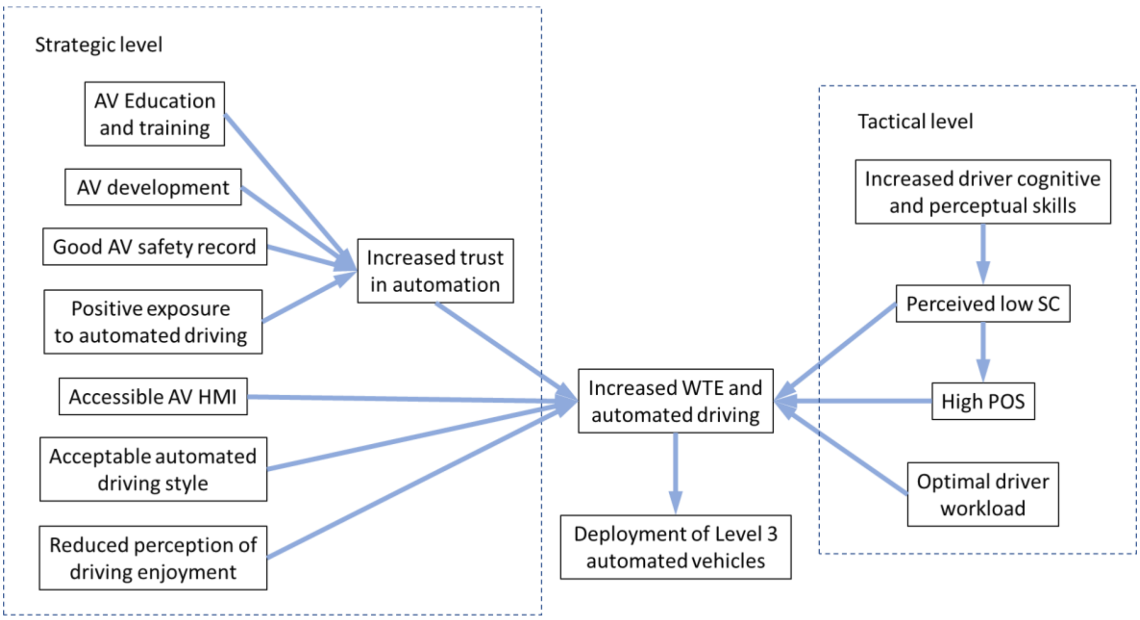


Figure 8.2 *Contributing factors to WTE and choice of automated vehicle control mode*

As seen above, several theoretical and practical implications from this work were identified in terms of WTE in a Level 3 automated vehicle, as were limitations in the research program and recommendations for future research. The introduction of Level 3 automated vehicles presents a significant challenge from a human factors perspective but this research shows that manipulation of WTE could be a tool to address several of these issues. This was arguably the first experimental research program dealing explicitly with this important topic and it provides several initial inroads into this important and safety-related issue.

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Appendices

Appendix A: Published journal paper:

Tomasevic, N., Horberry, T., Young, K. L., & Fildes, B. (2019). Validation of a driving simulator for research into human factors issues of automated vehicles. *Journal of the Australasian College of Road Safety*, *30*(2), 37–44.

Validation of a driving simulator for research into human factors issues of automated vehicles

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This peer-reviewed paper was first presented as an Extended Abstract and Oral Presentation at the 2018 Australasian Road Safety Conference (ARSC2018) held in Sydney, NSW, Australia and first published in the ARSC2018 Proceedings in the form of an Extended Abstract. It was expanded into a 'Full Paper' and underwent further peer-review by three independent experts in the field. It is being reproduced here with the kind permission of the authors and is now only available in this edition of the JACRS.

Key Findings

- The driving simulator is a valid tool for human factors research in automated vehicles;
- Events and conditions with the best transfer of behavioural validity have been identified;
- Findings will be used for the design of future studies investigating automated driving;
- Further simulator validation issues were identified, e.g. simulator representation of on-road situations requiring high mental workload.

Abstract

This study evaluated the behavioural validity of the Monash University Accident Research Centre automation driving simulator for research into the human factors issues associated with automated driving. The study involved both on-road and simulated driving. Twenty participants gave ratings of their willingness to resume control of an automated vehicle and perception of safety for a variety of situations along the drives. Each situation was individually categorised and ratings were processed. Statistical analysis of the ratings confirmed the behavioural validity of the simulator, in terms of the similarity of the on-road and simulator data.

Keywords

Vehicle automation, driving simulator, human factors, validation, willingness to resume control, perception of safety

Glossary

SAE – Society of automotive engineers
TH – Time headway
POS – Perception of safety
WTE – Willingness to engage automated driving system
WTRC – Willingness to resume manual control of the vehicle
TD – Traffic density
SC – Situation complexity

Introduction

Driving automation is on the brink of becoming the mainstream from a technological point of view. The SAE classifies six levels of automation. These levels are summarised in Figure 1, with the deployment predictions being derived from multiple sources such as Chan (2017) and Litman (2015). The majority of academic research found is focussed on levels 2 and 3. Level 3 is acknowledged as being associated with the greatest number of human factors issues because it requires the driver to remain in the loop enough to regain manual control in the event of an emergency or if driving conditions move outside of the automation operational design domain (Logan et al, 2017).

There are many unanswered questions from a human factors perspective that are preventing legalisation of automated driving, such as transfer of control from automated to manual driving and driver acceptance of new technology. These questions are difficult to answer without proper testing. The obvious approach to this problem is the utilisation of driving simulators. Simulators provide a

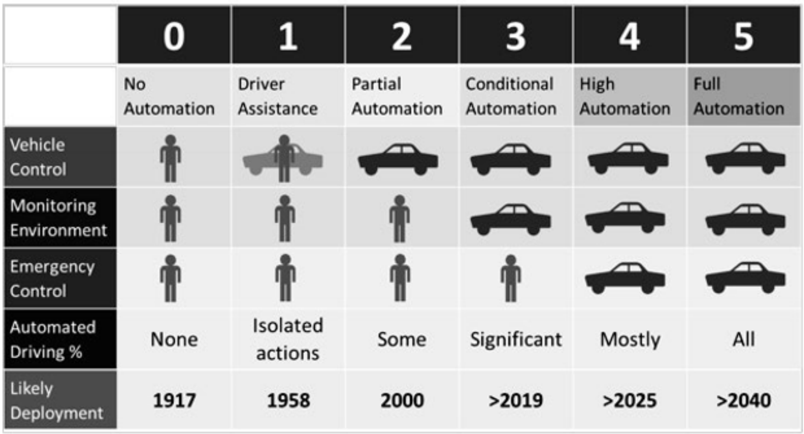

Figure 1. SAE levels of automation and deployment predictions

safe, economical and controlled environment in which to conduct automation research. However, this is an artificial environment and these differences may influence the subject's behaviour. Therefore, to be used in automation research, driving simulators need to reproduce similar driver responses to those occurring on the real road. Every driving simulator has its limitations which are directly related to the cues (visual, auditory tactile and vestibular) it is able to provide. Kaptain et al. (1996), state that if the set of cues important to the subject of the investigation is available in the simulator, the simulator may be as valid as a field experiment.

As research simulators are commonly developed independently of each other and have distinct parameters (Godley et al. 2002), it is necessary to validate them on an individual basis. Driving simulators are commonly validated for various specific aspects such as speed perception, vehicle dynamics, hazard perception and many more. Godley et al. (2002) evaluated a driving simulator for speed research establishing relative behavioural validity and relative validity for mean speed. McGehee et al. (2000) examined driver reaction and performance in an intersection crash scenario in the simulator and on a test track. The study produced statistically equivalent reaction times. Underwood et al. (2011) evaluated hazard perception in the simulator and on the road observing similar patterns in behaviour in both settings.

As automated driving is a new field, a study was needed to establish the behavioural validity of the available driving simulator. Behavioural validation involves:

- Comparison of two systems during identical tasks and circumstances in terms of system performance and/or driver behaviour
- Measurement of physical and/or mental workload (physiological measurements)
- Subjective criteria from drivers
- Evaluation of how well the simulator results align to real-world findings

There are very few studies concerning validity of the driving simulator for research into automated vehicles. Eriksson et al. (2017) explored workload differences between a driving simulator and on-road drives in an automated vehicle. In this validation study the authors argued that a driving simulator can be a valid tool for studying users' interactions with automated driving systems. Pariota et al. (2017) observed the effects of connected automated vehicles on car-following behaviour in driving simulators and an instrumented vehicle. Although there were some differences in behaviour between environments, a consistency in car spacing within each environment has been shown.

The current work is part of a larger investigation of human factors issues associated with automated driving. The overall research program aims to explore drivers' willingness to engage or disengage automated driving system, the perception of safety in automated driving and transfer of control between vehicle control modes. The aim of this study was to validate the use of a driving simulator for research in human factors of automated driving. More specifically, a relative behavioural validation study was conducted which will establish a level of credibility and transferability of the simulator results into the real world. To the knowledge of authors, no other validation study had been conducted to answer this specific question in the context of automated driving.

Method

The study was conducted at the Monash University Accident Research Centre. The data collection was conducted under semi-controlled experimental conditions. The on-road drive was conducted on real roads and in the real traffic but followed a strict route. The simulator drive was programmed to replicate this on-road test route in terms of length, road conditions and other controllable parameters. No safety critical events were part of the experimental drives.

Since an automated vehicle was not available for the study, on-road automated driving had to be controlled by the human driver. Therefore, to keep experimental conditions the same across the settings, participants were aware that a human driver was used to represent automation in both drives. The participants were placed in the passenger seat and did not have access to a steering wheel and control pedals in both conditions. The researcher was in the driver's seat and controlled the vehicle. Participants were instructed to assume a situation in which they were behind the controls of a level 3 automated vehicle that was operating in an automated mode for the entire duration of the drive and that they could resume manual control of the vehicle at any time, but their task was just to answer the experimenter's questions.

The same procedure was followed in the simulator. This way, both experimental conditions were kept as similar as possible. This included obstructing speedometer from the participant in the simulator since the speedometer in the car was not visible from the passenger's seat.

Participants

There were 20 participants, 11 males and 9 females, ranging in age from 21 to 64 years, with an average age of 36.8 years (SD = 11.2). The median number of years of driving experience was 14.5 (IQR: 9-24.75). Participants were recruited from both Monash University (post-graduate and undergraduate students or staff) and outside using personal contacts. Ethics approval was obtained from Monash University Human Research Ethics Committee. Participants were required to have a full driver's licence and drive at least 6,000 km per year. They were paid $30 for their participation. The total duration of the experiment was between 90 and 105 minutes.

Equipment

Instrumented car

The experimental car was an instrumented Holden Commodore VE. It had rear wheel drive and automatic transmission. In addition to the existing instrumentation, a wide-angle camera was used to record the driving scene and audio cues.

Driving simulator

The MUARC Automation Driving Simulator (Figure 2) consisted of two seats mounted on separate motion bases. Both seats moved in unison. The simulator vehicle represented a car with an automatic transmission. Visuals were presented on three 46" high brightness bezel-less displays. Each display had a resolution of 1080p and the image refresh rate was 60Hz.

The driver and the passenger both had a 140° of horizontal field of view and a 45° vertical field of view. The sound was presented via left, right and centre satellite speakers and a subwoofer. Each motion base produced three degrees of freedom of movement as well as vibration. The same wide-angle camera from the instrumented car was used to record simulator drives and audio cues.

Experimental questions

Figure 2. Automation driving simulator setup

A tablet (iPad) was used to collect answers during both simulator and on-road drives. There were between 20 and 25 questions for each drive and the final overall question completed after the end of drive. Each question consisted of part A and part B. Part A (Figure 3) asked participants to rate willingness to resume control of the vehicle in that situation. The four categories were: very willing, willing, unwilling and very unwilling. Part B (Figure 3) asked participants to rate perception of safety in that situation using a linear scale from 1 to 100 (1 for very unsafe and 100 very safe).

Figure 3. Example of Part A (Willingness to resume control) and B (Perception of safety) question at the decision point

Experimental Drives

The real road and simulator routes were selected to resemble each other as much as possible, taking into account available equipment, time constraints and resources. Overall factors that had to be considered were:

- The total duration of each drive needed to be kept under 30 minutes;
- Total travelled distance during drives needed to be limited to under 20 km;
- The proportion of freeway driving vs urban/residential driving had to be similar;
- Time of the day was between 11:00 and 15:00. This prevented sun glare situations and provided an optimum visibility on the road;
- Peak traffic conditions had to be avoided; and
- Adverse weather conditions had to be avoided (dry roads only).

The following matching criteria between on-road and simulator scenes were used:

- Road lane width;
- Speed limits;
- Number of roundabouts;
- Number of turns;
- Number of freeway entries and exits;
- Number of road bends;
- Traffic density and composition;
- Number of signalised intersections;

The simulator drives were scripted and therefore the same events were presented to each participant. However, during the on-road drives not all events were encountered by every participant. Only events that occurred in both the simulator and on-road drive were analysed.

Experimental Procedure

Participants completed an informed consent form and read the experimental instructions. They were then given a brief introduction to automated vehicles and presented with a definition of willingness:

- Ready of eager to do something;
- Disposed or inclined;
- Prepared, or
- Acting or ready to act gladly.

This was followed by a demographics questionnaire that also included questions about driving habits, subjective driving skills and attitudes toward technologies.

Participants completed the drives in a counterbalanced order. Half of the participants completed the simulator drive first and the other half completed the on-road drive first. Only one researcher was involved in the experiment.

During the drives, participants were given a tablet which was used to record ratings for willingness to resume control (WTRC) and perception of safety (POS). During the drives, participants were instructed to observe the road and wait for the researcher's verbal instruction: "Ready ... Now!". The instructions were given with enough lead time for participant to recognise the situation ahead. After hearing this cue, participants were instructed to stop observing the road and quickly complete Part A and Part B of the question. After completing the question, participants would continue observing the road until the next question.

At the end of the drives, participants were asked to rate their overall willingness to engage (WTE) automated driving system as well as their perception of safety of the entire drive.

Data Collection and Processing

During the drives, the following data were collected:

- Video recordings of the road scene;
- Experimental drive questionnaire;
- GPS and vehicle data in on-road drive only;
- Simulator data during simulator drive only;
- Pre-drive and post-drive well-being questionnaires (simulator only).

Using video recording, each decision point was coded for several parameters. They were: time, event name, environment, speed limit, road division, number of lanes, road shape, traffic density, situation complexity and participant comments. These parameters were later used in selecting data for statistical analysis. Traffic density and situation complexity of each event were rated as low, medium and high according to the criteria below.

Traffic density (criteria partially based on Strategic Highway Research Program 2, SHRP2) Levels of Traffic density (VTTI, 2015):

Low:

- Free flow, no lead traffic (0-1 cars ahead within 5s time headway (TH), minimum TH > 3s);
- Freedom to select speed, change lanes and make turns (No vehicles in left or right lanes relative to the participant within 20m radius).

Table 1. Percentages of events with Levels of Traffic Density (TD) and Situation Complexity (SC)

	TD Road	TD Simulator	SC Road	SC Simulator
Low	64.24%	70.45%	56.53%	57.39%
Medium	30.41%	20.34%	40.47%	28.91%
High	5.35%	8.99%	3.00%	13.49%

Medium:

- Free flow with some restriction (1-3 cars ahead within 5sTH, 2-3s TH);
- Freedom to select speed, change lanes and make turns (vehicle or vehicles in left or right lanes relative to the participant, within 10 – 20m radius).

High:

- Forced traffic flow conditions (3+ cars ahead within 5 seconds TH, minimum TH < 2s);
- Limited freedom to select speed, change lanes and make turns (vehicle or vehicles in left or right lanes relative to the participant, within 10m radius).

Situation complexity levels (partially based on Cabral et al., 2016):

Low:

- No significant cognitive processing is required (clear road, smooth and predictable traffic).

Medium:

- Some cognitive processing required (traffic ahead, approaching intersections or turns).

High:

- Medium to intensive cognitive processing required (dealing with vulnerable or unpredictable road users, complex intersections, aggressive drivers, reduced visibility);
- Critical decision making (merging, overtaking, potential emergency braking).

Based on these criteria, levels of traffic density (TD) and situation complexity (SC) were assigned to every individual event. Distributions of these levels across all events are presented in Table 1.

Data Analysis

The purpose of the statistical analysis was to determine whether there were differences between ratings (WTRC/WTE and POS) given for similar decision points in both experimental environments (simulator and on-road). Generalised Estimating Equations model was used for statistical analysis. This model is used to estimate the parameters of the generalised linear model with the possible unknown correlation between outcomes. It can be used for both ordinal (WTRC/WTE) and interval data (POS). The data analysis was done by comparing dependent variables (ratings for WTRC and POS recorded during experimental drives in two environments).

Processing of the data resulted in a single rating for each category (individual events and conditions) per participant. In the GEE models, participants were the subject variable and experimental environment (simulator or on-road) were independent variables. WTRC/WTE and POS were the dependent variables. In cases where multiple records existed for a category, the median value was used for ordinal variables (because the data were non-normally distributed) and the mean for linear variables. The correlation matrix that represented the within-subject dependencies was estimated as part of the model.

Results

Results of the data analysis are presented in Table 2. The table contains a list of all tests conducted on events and driving conditions. Results are primarily expressed as p-values for both WTRC (WTE for the Final question) and POS (Figure 4).

The results for the final questionnaire item, which represents overall WTE and POS ratings for the whole drive revealed that there were no significant differences across the on-road and simulator environments for both WTE ($p=0.315$) and POS ($p=0.324$).

There were no significant differences across environments for WTRC and POS ratings for free driving on the freeway, short time headway, left bend, roundabout, give way/stop sign, congestion, stopped bus, and pedestrians.

Mixed results were obtained for free driving on urban roads where POS was significantly different across the environments, while there was no significant statistical difference in WTRC. Events that produced significant statistical differences in both WTRC and POS were uphill road and merging on the freeway.

Statistical test on levels of traffic density (TD) and situation complexity (SC) indicated that there were no significant statistical differences between on-road and simulator environments. The only exceptions were WTRC for medium TD on the freeway where significant differences were found across environments ($p=0.018$) and POS for medium SC on the freeway ($p=0.045$).

Table 2. Test results

	Mean POS road	Mean POS simulator	SD road	SD sim	p(POS)	p(WTE/ WTRC)
Final Question	70.75	73.30	3.59	3.89	0.315	0.324
Free Driving (Freeway) ay) Freeway)	71.21	76.26	3.35	3.15	0.053	0.180
Free Driving (Urban)	69.08	75.75	3.29	2.98	**0.000**	0.143
Short Time Headway	48.15	52.35	5.54	5.96	0.517	0.06
Left Bend (Freeway)	75.79	76.51	3.41	3.42	0.811	0.210
Roundabout	67.96	62.84	5.98	5.45	0.340	0.739
Give Way/ Stop Sign	65.36	67.58	4.04	4.60	0.492	0.657
Merging (Freeway)	56.63	74.15	4.20	3.12	**0.000**	**0.002**
Changing Lanes	62.58	51.65	5.17	4.54	**0.033**	0.482
Congestion*	75.93	61.79	7.52	5.96	0.127	0.089
Stopped Bus*	67.73	53.95	6.44	6.56	0.109	0.191
Pedestrians*	56.16	61.45	7.49	5.20	0.309	0.300
Uphill road*	72.43	86.55	4.17	2.38	**0.000**	**0.015**
Low TD (Urban)	68.58	70.47	3.13	3.17	0.371	0.951
Medium TD (Urban)	64.42	63.54	4.05	4.78	0.808	1.000**
Low TD (Freeway)	73.48	72.75	2.67	3.45	0.796	0.065
Medium TD (Freeway)	56.53	55.86	4.54	4.83	0.815	**0.018**
Low SC (Urban)	71.05	73.72	2.90	3.10	0.259	0.191
Medium SC (Urban)	62.98	60.45	3.76	4.70	0.304	0.701
Low SC (Freeway)	73.05	76.40	2.59	3.39	0.125	0.187
Medium SC (Freeway)	56.70	63.38	4.47	3.80	**0.045**	0.216
High SC (Freeway)*	61.33	47.30	8.58	5.15	0.160	0.968

*Events that did not have a full dataset (< 50%)

**Repeated GEE model analysis with only two categories of WTRC (willing and unwilling)

Significant values ($p < 0.05$) are shown in bold.

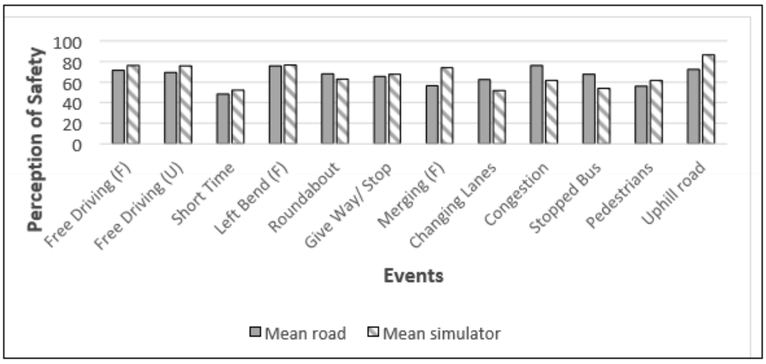

Figure 4. Perception of safety during events

Discussion

The results showed that for the large majority of events, there was no statistical difference ($p > 0.05$) in ratings of WTRC, WTE and POS when comparing the two driving environments. This suggests that these events are well represented in the simulator when compared to the on-road environment in the context of the research question. In their research on driving simulator validity, Kaptain et al. (1996), stated that if the results between the simulator and the field experiment are similar, the simulator is shown to be valid for investigating the studied driving task. Another important element of a succesful behavioural validation study is a carefully designed experimental procedure (Blana, 1996).

From the perspective of further research, it is more interesting to understand what were the differences in experimental conditions that may have contributed to the significant statistical differences. Only two events produced significant statistical differences in ratings for both POS and WTE between experimental conditions. They were merging onto the freeway and to a lesser extent unrestricted driving on an urban road.

Merging onto a freeway could be classified as a high-risk event. This event involved multiple simultaneous manoeuvres (changing lanes, adjusting speed, finding gaps, and continuously scanning the scene) while travelling at a relatively high speed, often in medium or high TD. In comparison with the on-road event, the simulator freeway merging event was simpler (lower TD) and more predictable, therefore demanding less mental workload. Moreover, we speculate that an increase in workload demand exponentially augments perceived risk between the two experimental conditions. Although the merging event in the simulator could be made more demanding by increasing traffic density and speed, further research is needed to answer how exactly perceived risk and mental workload correlate under the simulator and on-road conditions. The exact relationship will, of course, be affected by the specifications of each individual simulator.

Uphill driving on the urban road was intended as a relatively simple and undemanding event so the perceived risk should not be such an important factor. However, statistical test results indicated significant differences in the ratings between environments. Due to limitations in the selection of roads, not all experimental conditions could be accurately matched. In the simulator drive, this event occurred on the four-lane road, while in the on-road drive it occurred on a two-lane road with occasional parked cars on both sides of the road. To participants, the on-road event may have appeared less safe than the simulator event and thus, influenced their WTRC ratings. These observations are supported by Fildes et al. (1989) who found that road width and number of lanes had the strongest influence on judgements of safety and travel speed, while the roadside environment also had an effect but to a lesser degree. Finally, it is believed that the differences in WTRC for Medium TD on the freeway and POS for medium SC on the freeway are due to the challenges in creating a realistic freeway driving environment in the simulator.

It is important to accurately represent an event in the simulator; however, differences between the real and the simulated environments related to simulator measurements and mental workload emerge whatever the cost of a driving simulator is. Harms et al. (1996), observed that increasing the face validity of the VTI driving simulator did not necessarily enhance the overall behavioural validity of the simulator. More research is needed when investigating on-road situations that create a high mental workload and their representation in the simulator. This will be especially important in the case of take-over requests. In addition, it is important to understand the precise conditions under which drivers are willing to engage or disengage an automated driving system. A future study to investigate this is currently being undertaken by the authors.

Given that an automated vehicle was not available for this study and Level 3 Automated vehicles are not legally allowed to travel on Australian roads, we adopted a protocol whereby participants sat in the front passenger seat of the real and simulated vehicles which were driven by an experimenter. Participants were asked to imagine that he or she was in the driver's seat of an automated vehicle and answer the questions from this perspective. This method may, of course, lead to differences in participants' perception of safety and trust in vehicle automation. However, we estimate only a small impact of these limitations because the main task was to enter ratings in the questionnaire (willingness to resume control of the vehicle and perception of safety during the drive) and not to drive or respond to take over requests. We were also interested in comparing ratings across the on-road and simulated environments, which were kept as similar as possible in terms of the automation protocol.

Conclusions

The results confirmed the relative behavioural validity of the MUARC automated driving simulator. We argue that if certain limitations of the driving simulator are taken into account absolute behavioural validity can be confirmed.

These findings will be used for the design of future simulator experiments investigating willingness to resume control or engage an automated driving system, the associated perception of safety and driver behaviour during transfer of control.

Acknowledgements

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Appendix B: Introduction to automated vehicles (Studies 1, 3 and 4)

Introduction to Automated Vehicles

Automated Vehicles:

Automated vehicles are vehicles that perform the following functions without the driver's input:

- Steering (keeping the vehicle in the lane, changing lanes when necessary, making turns)
- Accelerating and decelerating (adjusting speed according to the speed limit, keeping the safe distance from vehicles in front)
- Monitoring the driving environment (continuously scanning what is happening around and making adjustments)

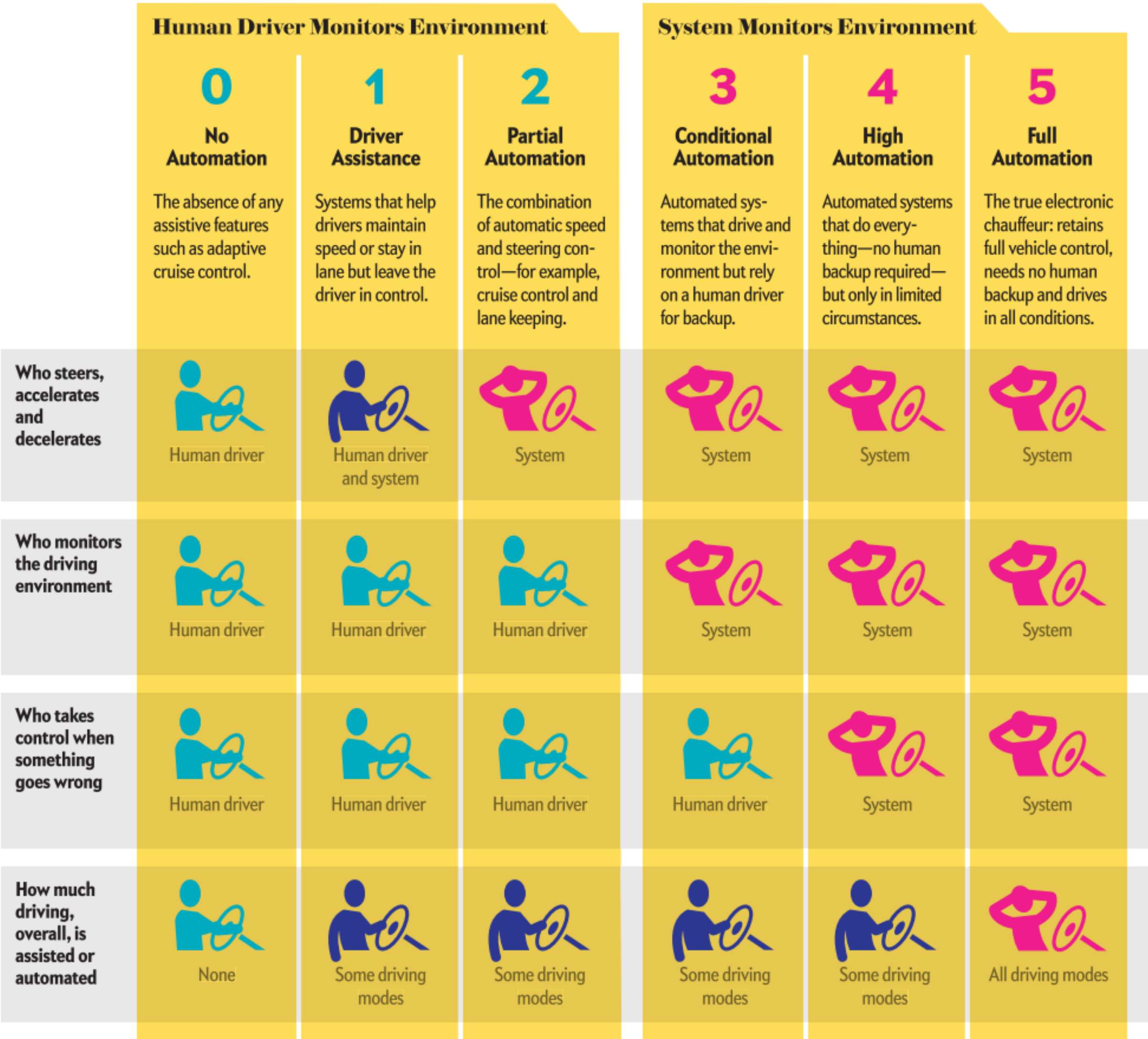

*Image copied from (Shladover, 2016)

Automated vehicles are still not widely available and regulated and therefore, for the purpose of this study, you will be driving a simulated automated vehicle in both automated and manual modes.

Appendix C: Pre-drive (Demographics) questionnaire for (all Studies)

MONASH University
Accident Research Centre

Pre-drive questionnaire

Participant code: ________________

Date: ________________

Thank you for coming along today. Your involvement is greatly appreciated. For research purposes, it is important that we obtain some information concerning your background. Please answer each question as fully and as accurately as possible, and remember, all of the information that you provide will be kept confidential.

Part A - Personal Details

Gender:

- ☐ Male
- ☐ Female

Age: ________

Do you suffer from any form of colour blindness or other vision problems?

- ☐ Yes
- ☐ No

Do you suffer from any form of physical disability?

- ☐ Yes
- ☐ No

Part B – Driving experience

How old were you when you were first licensed to drive a car? _________

Which car do you drive?
Brand: _________________
Model: _________________
Year: _________________

Transmission:
- ☐ Automatic
- ☐ Manual

Is your car equipped with any of these?
- ☐ Cruise Control
- ☐ GPS Navigation
- ☐ ABS
- ☐ Electronic Stability Control
- ☐ Adaptive Cruise Control
- ☐ Lane Keeping System
- ☐ Automatic Braking
- ☐ Automatic Parking
- ☐ Other
- ☐ None
- ☐ Don’t know

On average, how many hours do you spend driving a car each week? ___________

On average, how many kilometres do you drive each week? ___________

In which environment do you drive the most?
- ☐ Metropolitan
- ☐ Residential
- ☐ Rural

During an average week, in what traffic conditions do you spend most of your time driving?
- ☐ Heavy traffic conditions (e.g. peak hour)
- ☐ Medium traffic conditions (e.g. non-peak hour)
- ☐ Light traffic conditions (e.g. late at night)

How many car accidents (of any severity) have you been involved in within the last five years? ___

Part C – Subjective ratings

How confident are you in your general driving skills?

- ☐ Not Confident
- ☐ Somewhat confident
- ☐ Moderately confident
- ☐ Confident
- ☐ Very Confident

How safe driver you consider yourself to be?

- ☐ Very unsafe
- ☐ Unsafe
- ☐ Neutral
- ☐ Safe
- ☐ Very Safe

How enjoyable is a car driving for you?

- ☐ Not enjoyable
- ☐ Somewhat enjoyable
- ☐ Moderately enjoyable
- ☐ Mostly enjoyable
- ☐ Very enjoyable

What is your attitude towards new technologies/gadgets in vehicles?

- ☐ Very negative
- ☐ Negative
- ☐ Neutral – I don't know
- ☐ Positive
- ☐ Very positive

Would you trust an automated system (similar to autopilot on an aeroplane) to control a car for you, if your car was equipped with such a system?

- ☐ No trust at all
- ☐ Low trust
- ☐ Moderate trust
- ☐ Trust
- ☐ Complete trust

How would you rate yourself as an adopter of new technologies (e.g. smartphones etc.)?

- ☐ Very early adopter
- ☐ Early adopter
- ☐ Neither early or late - average
- ☐ Late adopter
- ☐ Very late adopter

Thank you.

Appendix D: Pre-drive automation questionnaire (Study 4)

MONASH University
Accident Research Centre

Pre-drive vehicle automation questionnaire

Participant ID: __________ Date: __/__/2019

1. What kind of vehicle automation systems would you be the most interested in using? Please choose one option.
- ☐ None
- ☐ Driver assistance systems such as various warnings, cruise control
- ☐ Conditional automation, such as driving on the highway with minimal actions required from the driver (driver needs to supervise automation)
- ☐ High automation without any actions required from the driver (No need to focus on driving)
- ☐ Full automation (manual driving is not available)

2. How often do you think you would use automated driving if your car was equipped with a Level 3 automation system (use the sliding scale)?

Never ———————————— All the time

3. Please indicate your preference of vehicle control mode for the following situations (use the sliding scale):

Straight roads:	Manual	————————	Automated
Winding roads:	Manual	————————	Automated
High traffic density:	Manual	————————	Automated
Familiar route:	Manual	————————	Automated
Unfamiliar route:	Manual	————————	Automated
Day driving:	Manual	————————	Automated
Night driving:	Manual	————————	Automated
Reduced visibility:	Manual	————————	Automated
Congestion:	Manual	————————	Automated
Roadworks:	Manual	————————	Automated
Complex intersection:	Manual	————————	Automated
School zone:	Manual	————————	Automated
Pedestrians on crossing:	Manual	————————	Automated

Freeway merging:	Manual	Automated
Overtaking on freeway:	Manual	Automated
Low speed limit (40km/h):	Manual	Automated
Residential roads:	Manual	Automated
City driving:	Manual	Automated
Arterial roads:	Manual	Automated
Country roads:	Manual	Automated
Freeway	Manual	Automated

Thank you.

Appendix E: Post-drive automation questionnaires (Study 4)

MONASH University
Accident Research Centre

Post-drive Vehicle automation questionnaire

Participant ID: __________   Date: __/__/2019

1. Tell us your reason for generally picking Automated or Manual driving mode. Do you have any specific choices that you made?

   ____
   ____
   ____
   ____

2. What kind of vehicle automation systems would you be the most interested in using? Please choose one option.
   - ☐ None
   - ☐ Driver assistance systems such as various warnings, cruise control
   - ☐ Conditional automation, such as driving on the highway with minimal actions required from the driver (driver needs to supervise automation)
   - ☐ High automation without any actions required from the driver (No need to focus on driving)
   - ☐ Full automation (manual driving is not available)

3. How often do you think you would use automated driving if your car was equipped with a Level 3 automation system (use the sliding scale)?

   Never ______________________________ All the time

4. Please indicate your preference of vehicle control mode for the following situations (use the sliding scale):

Straight roads:	Manual	______________________________	Automated
Winding roads:	Manual	______________________________	Automated
High traffic density:	Manual	______________________________	Automated
Familiar route:	Manual	______________________________	Automated
Unfamiliar route:	Manual	______________________________	Automated
Day driving:	Manual	______________________________	Automated
Night driving:	Manual	______________________________	Automated

Reduced visibility:	Manual	Automated
Congestion:	Manual	Automated
Roadworks:	Manual	Automated
Complex intersection:	Manual	Automated
School zone:	Manual	Automated
Pedestrians on crossing:	Manual	Automated
Freeway merging:	Manual	Automated
Overtaking on freeway:	Manual	Automated
Low speed limit (40km/h):	Manual	Automated
Residential roads:	Manual	Automated
City driving:	Manual	Automated
Arterial roads:	Manual	Automated
Country roads:	Manual	Automated
Freeway:	Manual	Automated

5. Has your opinion of vehicle automation changed after this study?

- ☐ Significantly more positive
- ☐ More positive
- ☐ No change
- ☐ More negative
- ☐ Significantly more negative

Thank you.

Appendix F: Qualitative analysis of subjective reasons for selection of vehicle control mode (Study 4)

Introduction

This section describes a qualitative analysis of the reasons given by participants for choosing the automated or manual vehicle control mode in Study 4, supplementing the investigation of the main research question. At the end of each experimental session, participants were asked to provide subjective reasons for selecting Automated or Manual driving mode generally throughout the drive and whether they made any specific choices. They were also encouraged to make other comments.

Wong (2008) defined qualitative data analysis as *"the process of systematically searching and arranging the interview transcripts, observation notes, or other non-textual materials that the researcher accumulates to increase the understanding of the phenomenon"* (p. 1), Generally, the key stage of this process is coding or categorising the data according to identified patterns or themes.

Categorisation of participants' comments

As the first step of this analysis, each answer was converted into a shorter form and allocated to one of the categories. This was done separately for reasons given for selecting automated vehicle control mode and for selecting manual vehicle control mode. Results are summarised in **Table F.1**.

Table F.1 *Summary of reasons for selecting vehicle control mode*

Reasons for selecting automated control	Reasons for selecting manual control
• When trusting AS (6) • When feeling safe (3) • Generally comfortable • Curious to try (2) • Never (2) • On clear or straight roads (7) • In simple situations (3) • For driving comfort (2) • Always (2) • In reduced visibility (9) • On unfamiliar roads • In difficult driving conditions • When perceived situation as more dangerous • In complex situations	• At intersections (5) • In high complexity situations (2) • In rain and fog • When facing oncoming traffic • When facing obstacles on the road • When not trusting AS (10) • In less safe conditions (2) • Around unpredictable road users (3) • In less predictable situations • In uncertain conditions (2) • To prevent falling asleep • In simple situations (4) • In low complexity • Always (4) • For driving enjoyment (2)

The number in parentheses indicates the number of participants that gave this particular answer. The next step of this analysis was the recognition of common themes among these reasons and further categorisation.

Identification of themes among reasons for choosing automated driving

The logic and the outcome of this step in the analysis of reasons for choosing automated driving is illustrated in **Figure F.0.1**. All given reasons for selecting automated control mode are listed on the left side with the number of participants that gave a particular reason indicated in parentheses. Seven logical themes were identified and listed on the right side of the diagram. The categorisation logic is illustrated with the use of AND gates.

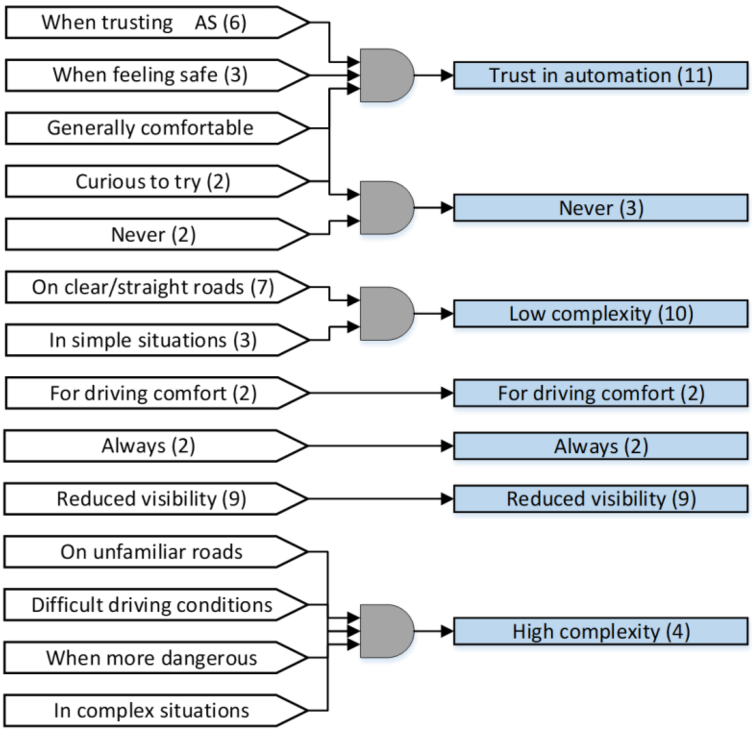

Figure F.0.1 *Illustration of logic for identifying themes of reasons for selecting an automated control mode*

Six participants reported that they would select automated mode when trusting the AS (automated system), three when feeling safe, one was comfortable with automation and one was curious to try but based the decision on trust. All these reasons were classified under a common theme of **trust in automation**, accounting for eleven participants.

Two participants stated they would never select an automated driving mode, while one of them was curious to try automated driving. Therefore, three participants were classified as non-users of vehicle automation (**Never**).

For ten participants, **low complexity** was the theme for selection automated driving mode (driving on straight roads and in simple situations). This theme was kept separate from trust in automation at this stage of analysis, due to the relatively high proportion of reasons identifying complexity.

Four participants gave **high complexity** as a reason to switch to automated driving mode.

Two participants reported that they would **always** use automated driving mode while two participants would use automation for driving comfort. Nine participants selected the automated driving mode during **reduced visibility**. The participants mainly referred to driving in rain and fog experienced in experimental drives.

The distribution of participants for each theme is illustrated in **Figure F.0.2**.

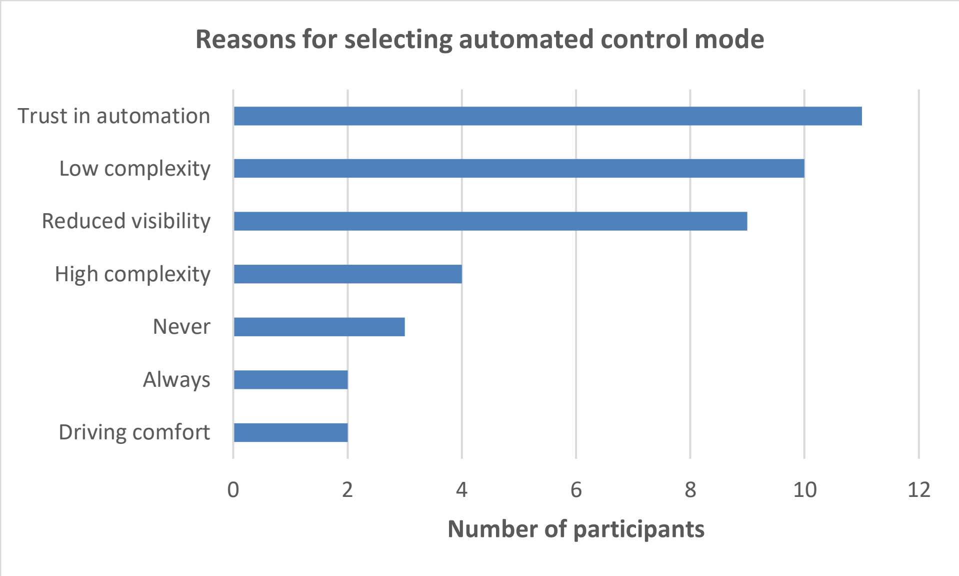

Figure F.0.2 *Distribution of participants for each theme of reasons for selecting an automated driving mode*

Identification of themes among reasons for choosing manual driving

Similarly, all given reasons for selecting automated control mode by participants are listed on the left side of **Figure F.0.3**, with the number of participants that gave a particular reason indicated in parentheses. Six logical themes were identified and listed on the right side of the diagram. The categorisation logic is illustrated with the use of AND gates.

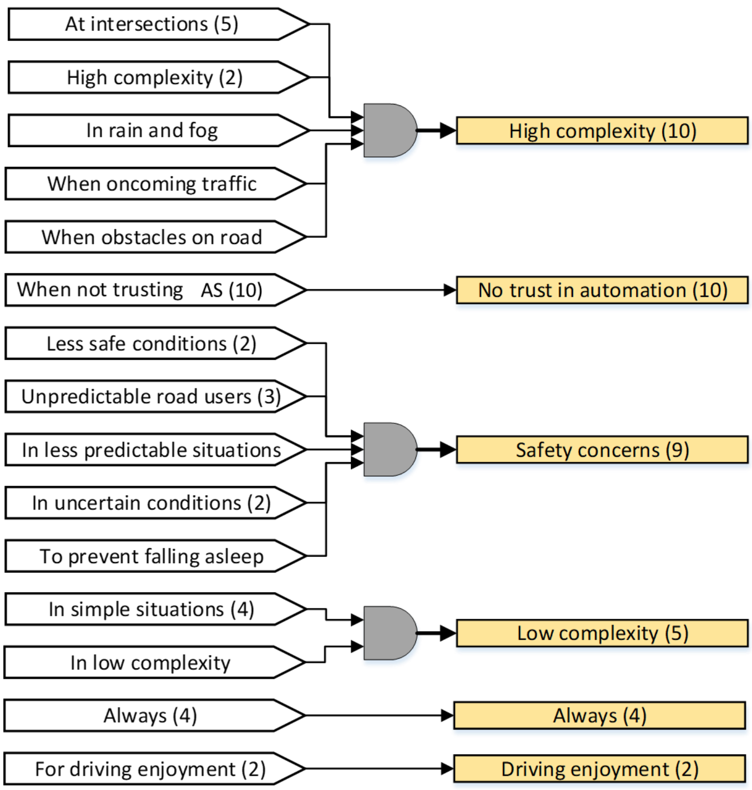

Figure F.0.3 *Reasons for selecting a manual driving mode*

Ten participants identified increased complexity of driving situations, as a reason to choose the manual driving mode. Five participants singled out intersection was complex while rain and fog, facing oncoming traffic and obstacle on road were reasons given by one participant each. Two participants directly identified high complexity. Therefore, they were classified into a **high complexity** theme.

Ten participants specifically stated that they chose manual driving mode when not trusting an automated driving system therefore confirming the theme of **trust in automation**.

Nine participants considered various aspects of safety to be the main reason for choosing manual driving mode resulting in **safety concerns** theme. These were unsafe driving condition, unpredictable road users, unpredictable situations or conditions and subjective concern of falling asleep in automated driving mode.

Four participants would **always** use manual driving mode, therefore rejecting automation. For two participants a **driving enjoyment** is the main reason to select manual driving mode. Five participants would use manual driving mode only in less complex driving situations hence being classified in a **low complexity** theme. The distribution of participants for each theme is illustrated in **Figure F.0.4**.

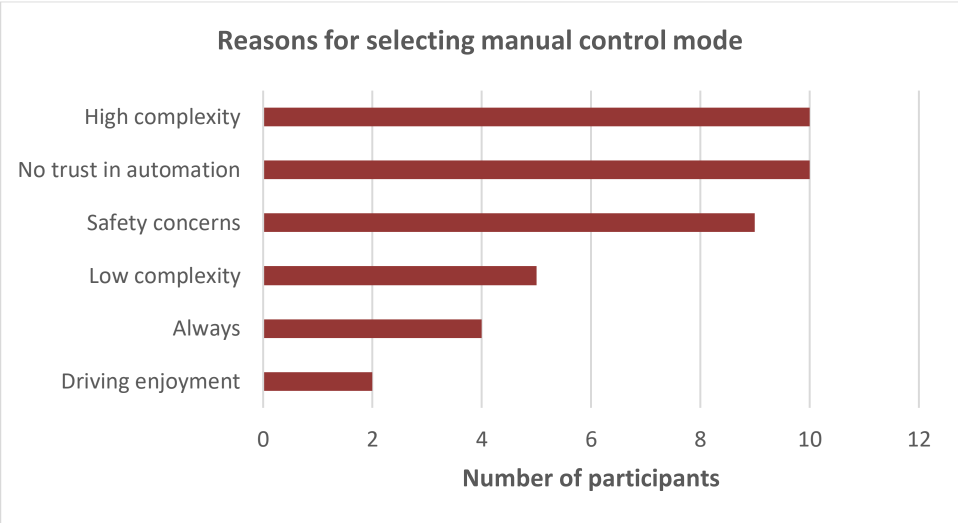

Figure F.0.4 *Distribution of participants for each theme of reasons for selecting manual control mode*

Identification of major determinants

The final step of this analysis was the identification of major determinants that are used in the selection of vehicle control mode. All reasons for selecting an automated driving mode (highlighted in blue) and all the reasons for selecting manual driving mode were (highlighted in yellow) were listed on the left side of the diagram and grouped by common traits. These subgroups were merged using OR gate logic. The results are presented in **Figure F.0.5**.

The majority of participants (54%) based their choice on the evaluation of their trust in an automated driving system. Ten participants (24%) based their choice on subjective confidence in their driving skills. Five participants (12%) based their choice on their lack of driving confidence. Four participants (10%) rejected the automated driving option.

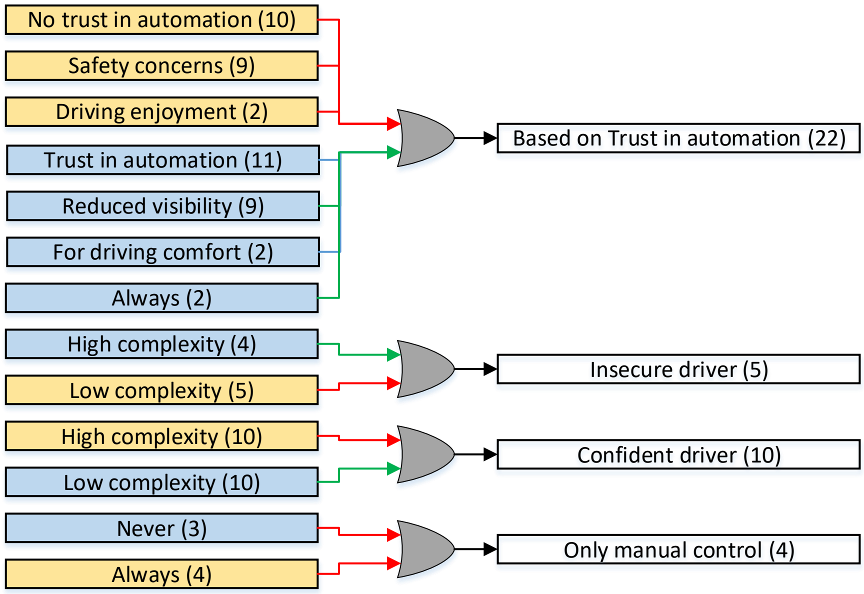

Figure F.0.5 *Merging themes for selection of control mode*

Two major determinants were identified from these groups. The first one was **trust in automation**. The second major determinant was **driver confidence** or self-confidence (an insecure driver is the opposite of a confident driver and preference for manual control only was associated with high driver confidence).

Additional participant comments

Additional participant comments given at the end of Study 4 are summarised in **Table F.2**.

Table F.2 *Additional participants' comments from Study 4*

#	Comment
1	"I noticed that I was getting complacent at times".
2	"Working in IT, I am reluctant to rely on technology to control driving."
3	"I don't want to become complacent, therefore I prefer Level 3 automation"
4	"I am not certain about higher levels of automation until I see it work."
5	"If given the choice I want to be the driver."
6	"Travelling in automated mode feels twice as long."
7	"At some places automation did a better job than I would."
8	"A couple of times I wanted to use automation but couldn't be bothered."
9	"It is so hard not to hold the steering wheel in automated mode."
10	"I thought it was better to leave the man in charge, didn't want to make a change"

Appendix G: The hysteresis effect on the choice of vehicle control mode in a Level 3 automated vehicle (Study 4)

This Appendix proposes a consideration of the hysteresis factor in the choice of vehicle control mode in Level 3 automated vehicle. A well-known phenomenon in physics, the hysteresis effect has also been investigated in human factors research such as information processing (Farrell, 1999) and should be considered when designing equipment, procedures and training. Farrell (1999) stated that *"a system is said to exhibit hysteresis when it responds differently to identical inputs depending on the direction in which the system is being driven."* (p. 1). Therefore, based on several participant comments (Appendix F) and existing theories, it is likely that hysteresis could be a factor in the choice of control mode in Level 3 automated vehicles. A simplified explanation of the hysteresis effect applied to the probability that a specific vehicle control mode would be selected is illustrated in **Figure G.6**.

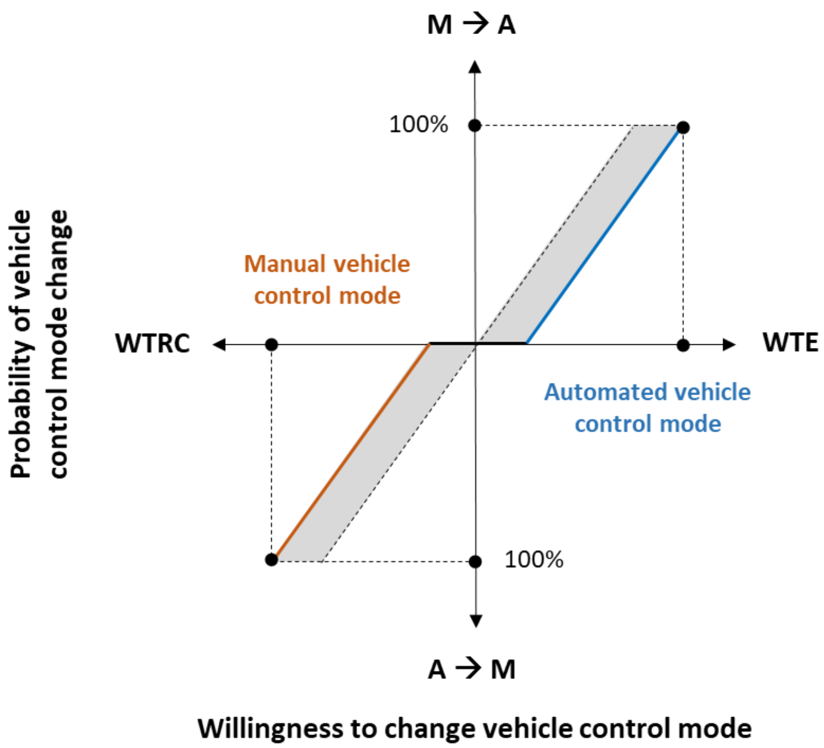

Figure G.6 *Illustration of a hysteresis effect in the change of Level 3 automated vehicle control mode*

The horizontal axis represents a driver's willingness to change vehicle control mode representing both WTE and WTRC, dependent on the active vehicle control mode. The vertical axis represents the probability of change of vehicle control mode. The blue line is a relation between the level of drive's WTE and the probability of change from manual to automated vehicle control mode, the brown line is the relation between driver's WTRC and the probability of changing vehicle control mode from automated to manual.

For illustration purpose, the hysteresis effect is simply shown as a horizontal shift (grey area) in the level of willingness (WTE/WTRC) required to overcome the perceived effort required for changing vehicle control mode. The exact relationship between willingness to change and the probability of making change is most likely more complex (non-linear) and should be further explored.