Innovation Report

ENGINEERING DOCTORATE

INFORMATION REQUIREMENTS FOR FUTURE HMI IN PARTIALLY AUTOMATED VEHICLES

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GLOSSARY

ADAS	Advanced Driving Assistance Systems
AHFE	Applied Human Factors and Ergonomics
AI	Artificial Intelligence
ANOVA	Analysis of Variance
BSI	British Standards Institute
BSREC	Biomedical & Scientific Research Ethics Committee
BUC	Built-Up Cab
DDT	Dynamic Driving Task
DRS	Design Research Society
EAST	Event Analysis of Systematic Teamwork
EngD	Engineering Doctorate
GPS	Global Positioning Service
HIP	High Information Preferences
HMI	Human Machine Interface
IEEE	Institute of Electrical and Electronics Engineers
IMC	International Manufacturing Centre
IUS1/2	Information Usage Study 1 & 2
LGP	Long Glance Proportion
LIDAR	Light Detection and Ranging
LIP	Low Information Preferences
MSGD	Mean Single Glance Duration
NHTSA	National Highway Traffic Safety Administration
ODD	Operational Design Domain
OEDR	Object Event Detection and Response
PNG	Portable Network Graphics
PST	Primary Secondary Tertiary
SAE	Society of Automotive Engineers
SMI	SensoMotoric Instruments
SRK	Skills Rules Knowledge
ST	System Transparency
TC	Technical Competence
TEORT	Total Eyes Off-Road Time
TM	Trust Model
UI	User Interface
UNECE	United Nations Economic Commission for Europe
UX	User Experience
3xD	WMG 3xD Simulator

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Abstract

Partially automated vehicles are increasing in prevalence and enable drivers to hand over physical control of the vehicle's longitudinal and latitudinal control to the automated system. However, at this partial level of automation, drivers will still be required to continuously monitor the vehicle's operation and take back control at any time from the system when required. The Society of Automotive Engineers (SAE) defines this as Level 2 automation and consequently a number of design implications arise.

To support the driver in the monitoring task, Level 2 vehicles today present a variety of information about sensor readings and operational issues to keep the driver informed; so appropriate action can be taken when required. However, existing research has shown that current Level 2 HMIs increase the cognitive workload, leading to driver cognitive disengagement and hence increasing the risk to safety. However, despite this knowledge, these Level 2 systems are available on the road today and little is known about what information should be presented to drivers inside these systems. Hence, this doctorate aimed to deliver design recommendations on how HMIs can more appropriately support the driver in the use of a partially automated Level 2 (or higher) vehicle system. Four studies were designed and executed for this doctorate.

Study 1 aimed to understand the information preferences for drivers in a Level 2 vehicle using semi-structured interviews. Participants were exposed to a 10 minute, Level 2 driving simulation. A total of 25 interviews were conducted for first study. Using thematic analysis, two categories of drivers: 'High Information Preference' (HIP) and 'Low Information Preference' (LIP) were developed. It was evident that the drivers' expectations of the partial automation capability differed, affecting their information preferences and highlighting the challenge of what information should be presented inside these vehicles. Importantly, by defining these differing preferences, HMI designers can be more informed to design effective HMI, regardless of the driver's predisposition.

Building on this, an Ideas Café public engagement event was designed for Study 2; implementing a novel methodology to understand factors of trust in automated vehicles. Qualitative data gathered from the 35 event attendees was analysed using thematic analysis. The results reaffirmed the importance of the information presented in automated vehicles. Based on these first two studies, it was evident that there was an opportunity to develop a more robust understanding of what information is required in a Level 2 vehicle.

Information requirements were quantitatively investigated through two eye-tracking studies (Studies 3 and 4). Both used a novel three- or five-day longitudinal study design. A shortlist of nine types of information was developed based on the results from the first two studies, regulatory standards and collaborations with Jaguar Land Rover experts. This was the first shortlist of its kind for automated vehicles. These 9 information types were presented to participants and eye-tracking was used to record their information usage during Level 2 driving. Study 3 involved 17 participants and displayed only steady state scenarios. Study 4 involved 27 participants and introduced handover and warning events. Across both studies, information usage changed significantly, highlighting the methodological importance of longitudinal testing over multiple exposures. Participants increased their usage of information confirming the vehicle's current state technical competence. In comparison, usage decreased of future state information that could help predict the future actions of the vehicle. By characterising the change in information usage, HMI designers can now ensure important information is designed appropriately. Notably, the 'Action Explanation' information, that described what the vehicle was doing and why, was found to be consistently the most used information. To date, this type of information has not been observed on any existing Level 2 HMI. Results from all four studies was synthesised to develop novel design recommendations for the information required inside Level 2 vehicles, and how this should be adapted over time depending on the driver's familiarity with the system and driving events.

This doctorate has contributed novel design recommendations for Level 2 vehicles through an innovative methodological approach across four studies. These design recommendations can now be taken forward to design and test new HMIs that can create a better, safer experience for future automated vehicles.

Acknowledgements

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Arun

Publications from this Doctorate

Journals

Ulahannan, A. et al. (2020) 'User expectations of partial driving automation capabilities and their effect on information design preferences in the vehicle', Applied Ergonomics, 82, p. 102969. doi: https://doi.org/10.1016/j.apergo.2019.102969.

Ulahannan, A. et al. (2020) 'Designing an Adaptive Interface: Using Eye Tracking to Classify How Information Usage Changes Over Time in Partially Automated Vehicles', IEEE Access, 8, pp. 16865–16875. doi: 10.1109/ACCESS.2020.2966928.

Ulahannan, A., Birrell, S., Jennings, P and Thompson, S. 2019 Designing an Adaptive Interface: How Information Usage changes following Handover and Warning Evens in a Partially Automated Vehicle **[Under Review]**

Peer-Reviewed Conferences

Ulahannan, A., Cain, R., Dhadyalla, G., Jennings, P., Birrell, S., Waters, M. and Mouzakitis, A., 2018 Using the Ideas Café to Explore Trust in Autonomous Vehicles. In International Conference on Applied Human Factors and Ergonomics (pp. 3-14). Springer, Cham.

Ulahannan, A., Cain, R., Dhadyalla, G., Jennings, P., Birrell, S., Waters, M. 2018 The Ideas Café: engaging the public in design research. In Proceedings of DRS 2018: Catalyst Vol. 1 (p.1175-1193).

Ulahannan, A., Birrell, S., Thomson, S., Skyrpchuk, L., Mouzakitis, A., 2019. The interface challenge for semi-automated vehicles: how driver behaviour and trust influence information requirements over time. Intelligent Vehicles Symposium 96–101.

Book Chapters

Ulahannan, A., Birrell, S., Thomson, S., Skyrpchuk, L., Mouzakitis, A., 2019. The interface challenge for partially automated vehicles: how driver characteristics affect information usage over time. Book on Human Factors in Intelligent Vehicles **[Accepted]**

Declaration

I hereby declare that all of the work contained in this report was produced by the author and that none of the work has been previously submitted for an academic degree.

All sources of quoted work have been referenced accordingly.

[redacted]

Arun Ulahannan

11th October 2019

1. Introduction

"As far as the user is concerned, the interface is the product."

Jeff Raskin (Raskin, 2000)

When a driver uses their vehicle, their acceptance and perceptions of the product are dependent on multiple factors. Some of those factors will be objective, like the performance of the vehicle, how economical it is or perhaps its age or mileage. However, many of the factors are likely to be subjective, such as how the vehicle 'feels' or the sound of the engine or doors. Perhaps the use of particular colours or how the vehicle's interface is laid out can all influence a user's perceptions. Research has shown that an emotional response is triggered whenever a user interacts with technology of any kind, and this is an essential consideration in the design of interfaces (Scheirer et al., 2002).

The field of designing for and understanding this emotional response is known as 'User Experience', and has been defined as "*the constant stream of self-talk that happens while we are conscious*" (Forlizzi & Battarbee, 2004, p. 263). This definition encompasses the users' emotional response to technology (Hassenzahl, 2018). A user who responds positively to their interaction with technology is understandably more likely to have higher satisfaction and acceptance of the technology (Erevelles, 1998). This is something that technology should strive to achieve; a good user experience that leads to higher satisfaction and hence acceptance of the technology. However, user experience is a holistic entity that can be difficult to measure; consisting of many different facets (González-Pérez et al., 2018; Schulze & Krömker, 2011). Consequently, specific, measurable areas of user experience need to be considered (specifically in the context of vehicles)- such as usability design.

As a subset of user experience, usability can be quantified and has been a driving force in the development of design guidelines for vehicle safety. For example, the NHTSA Total-Eyes-Off-Road-Time (TEORT) was a result of usability studies in driver distraction and workload (NHTSA, 2012).

While this is just one example of a usability guideline; the principle of usability design is that a design can be considered a success if these factors have been achieved. Further, this should be considered not only at a single point in time, but over a period of time (Bevan, 2009; Ketola, 1997). By understanding usability principles, better designs can be generated, that are easier to use and hence create more effective relationships between the user and the technology.

The unifying focus under which the elements of user experience and usability are practically applied is the Human Machine Interface (HMI). HMI research has traditionally been focussed on the development of technology and features, but the field has moved on recently to include a wider understanding of the principles of the user experience and usability of a driver's interaction with a vehicle (François et al., 2017). Hence, hereinafter, the interfaces within the vehicle will be referred to as 'HMI'.

One area where HMI research is becoming increasingly important is in the automotive industry, where numerous challenges are yet to be solved. For example, driver distraction and inattention are still a leading cause of road accidents in vehicles (Gershon et al., 2019; Regan et al., 2011). There are HMI challenges, such as the increasing adoption of touchscreens in vehicles (S. Becker et al., 2014), despite the issues of increased workload and visual-attentional demand (Cockburn et al., 2018; Large et al., 2018). A better understanding of HMI design can not only create a more pleasant and enjoyable experience for users (by contributing to the user experience) but also create systems that are safer and more useable (Jia et al., 2018; Lobo et al., 2018; Tokody et al., 2018). Furthermore, significant changes are predicted for the automotive industry.

In recent years, the automotive industry has been the focus of a high level of research interest. Mary Barra, CEO of General Motors, was quoted as saying "*...the auto industry will change more in the next 5 to 10 years than it has in the last 50"* (Barra, 2016). While the timescales of change are debatable, there has undoubtedly been significant progress on four key areas of the automotive industry (McKinsey, 2016):

1. Diverse Mobility: people are becoming increasingly mobile with more transport options available.
2. Connectivity: vehicles are becoming more connected and are tending towards a future where all vehicles can communicate with each other.
3. Electrification: by 2030, half of all vehicles sold in the UK must be a low emissions vehicle.
4. Automation: vehicles are increasingly able to cope with more of the driving task

For this doctorate, the development of vehicle automation was chosen as the research focus. This was for a number of reasons: it was one of the key areas of development identified by McKinsey (2016). It has also become increasingly prevalent on roads today with systems such as Tesla's Autopilot (Endsley, 2017) and Cadillac's Super Cruise (P. Olsen, 2018). Hence, it became evident that there were numerous research challenges in the area of automated vehicles that were of interest.

The aforementioned automated vehicle systems by, for example, Tesla and Cadillac are known as Level 2 partial automation. Level 2 is one of six levels defined by the SAE and these can be seen below in Figure 1.

SAE Level	Lateral & Longitudinal Control	OEDR	DDT Fallback	ODD
Level 0	User	User	User	-
Level 1	User/System	User	User	Limited
Level 2	System	User	User	Limited
Level 3	System	System	User	Limited
Level 4	System	System	System	Limited
Level 5	System	System	System	Unlimited

FIGURE 1 LEVELS OF AUTOMATION ADAPTED FROM (SAE, 2018) [1]

At the time of writing, the industry is developing vehicles at Level 1 and 2 of the SAE levels of automation (Banks, Eriksson, et al., 2018; Shutko et al., 2018). At Level 2 partial automation, the vehicle can control both the lateral and longitudinal direction of the vehicle, but the driver is expected to monitor the driving task. At Level 3, the critical difference is that there is no expectation on the driver to monitor the driving task when it is operating in its Operational Design Domain (ODD); but the driver should be ready to intervene at any time to a request from the system. At Level 4, the ODD is still limited, but there is now no expectation on the driver to be able to respond to handover requests from the system at any time. At the highest level of automation, Level 5, the vehicle is expected to feature an unlimited ODD with full driving automation.

By 2025, reports predict 8 million partially automated vehicles (Level 3 to 4) will be on the roads (Romeo, 2018), with some predictions estimating L3-L5 technology comprising 31% of total automotive sales by 2035 (Catapult, 2017). The challenges of the transition to automated vehicles are expected to increase and become more difficult to solve (Muller, 2016; Newcomb, 2012). Partially automated levels of driving face many of the same challenges to solve as vehicles today; such as increased cognitive workload and driver inattention (Banks & Stanton, 2016; Rafferty & Stanton, 2017; G. H. Walker et al., 2010). However, being a partially automated vehicle means the solutions to addressing these issues are different and, in many cases, more challenging. Fundamentally, it is recognised that asking human drivers to pay attention to the performance of a partially automated vehicle in operation is difficult, and this has been observed in many other

[1] Where OEDR is Object and Event Detection Response, DDT is the Dynamic Driving Task and ODD is Operational Design Domain

automated monitoring contexts for many years (Brookhuis et al., 2001; Dzindolet et al., 2003; Kaber & Endsley, 2004; Sheridan, 1995). As vehicles take over more control of the driving task, the driver's ability to monitor and ensure the safe operation of the vehicle becomes increasingly important. The promise of automated vehicles has much potential, but in its current stage of development, it places the drivers in a new role as monitors of a system. Hence how the design of the communication between the driver and the vehicle becomes essential to the safe and enjoyable use of these new vehicles (Choi & Ji, 2015; Endsley, 2016; Schaefer et al., 2016). However, to define the appropriate HMI requirements, there remain many open research questions, such as: what information should the vehicle be presenting to the driver? Moreover, do these information requirements change at different levels of automation?

It is here where it is important to distinguish the difference between what is referred as 'current' HMI and 'future' HMI. As discussed in the previous paragraph, evidently there are new challenges that the HMI must address in vehicles where there is an element of shared responsibility (Figure 1). From Level 2 onwards, elements of the driving task become increasingly automated, requiring the provision of information not previously required. Hence, it is at this point where 'future' HMI can be defined- HMI that must provide information supporting the driver in the shared responsibility of the overall driving task.

With partially/conditionally automated vehicles becoming more prevalent on roads, it is becoming evident that the future HMIs presented inside them do not provide the appropriate support to the driver. For example, there have been four confirmed fatalities that have involved Tesla's Level 2 system (Bachman, 2019). In all of these cases, the evidence would suggest that the system was used outside of its ODD and that the HMI did not communicate effectively with the driver to prevent the misuse of the system. Using cognitive modelling techniques, responsibility for these crashes are increasingly being attributed to the failing of the HMI, rather than the driver (Banks, Plant, et al., 2018). This challenge of supporting the driver through the internal HMI in the vehicle to use these systems more appropriately. Even at the conditional automation Level 3, the driver is required to be able to take over control of the driving task when notified.

Given these challenges facing partially automated vehicles, there is an evident need to understand how future HMIs in partially automated vehicles can be designed to more appropriately support the driver. It is recognised that in order to develop solutions and a contribution to any new area, the theoretical elements of why, what, when, where, how and who must be answered (Whetten, 1989). When applied to the challenge of designing HMIs for partially automated vehicles, the following questions arise:

- Why is the information currently presented in partially automated vehicles a problem?
- What information should be presented?
- When should the information be presented?
- Where should this information be presented?
- How the information should be presented?

- Who are the users of automated vehicles?

These five questions summarise the challenges that can be addressed through research. Arguably, the questions represent a chronological approach to addressing the design of partially automated vehicle HMI; before questions around where and how information should be presented, there must first be an understanding of what should be presented. Hence, the project initially addressed this breadth of questions, but as will be described in section 1.3, the focus was quickly made into understanding what information should be presented and hence the visual aspects of HMI design. Other modalities, such as sound or haptics, align with questions around *how* the information should be presented and hence were out of scope for this project's focus.

1.1. Aim

This doctorate aimed to understand how HMIs can more appropriately support the driver in the use of a partially automated Level 2 (or higher) vehicle system.

1.2. Objectives

1. To understand the prominent challenges in designing HMIs for partially automated vehicles.
2. To understand driver information preferences inside partially automated vehicles
3. To define the types of information required for future partially automated vehicle HMIs.
4. To understand how the usage of these types of information change with increased familiarity with the system and after driving events
5. To develop design recommendations for what information should be presented inside future partially automated vehicles and how this can be adapted over time and according to different driving events.

1.3. Research Project Structure

This section will detail each of the submissions in this doctorate and how they addressed the challenges in the area. The research doctorate structure is illustrated below in Figure 2.

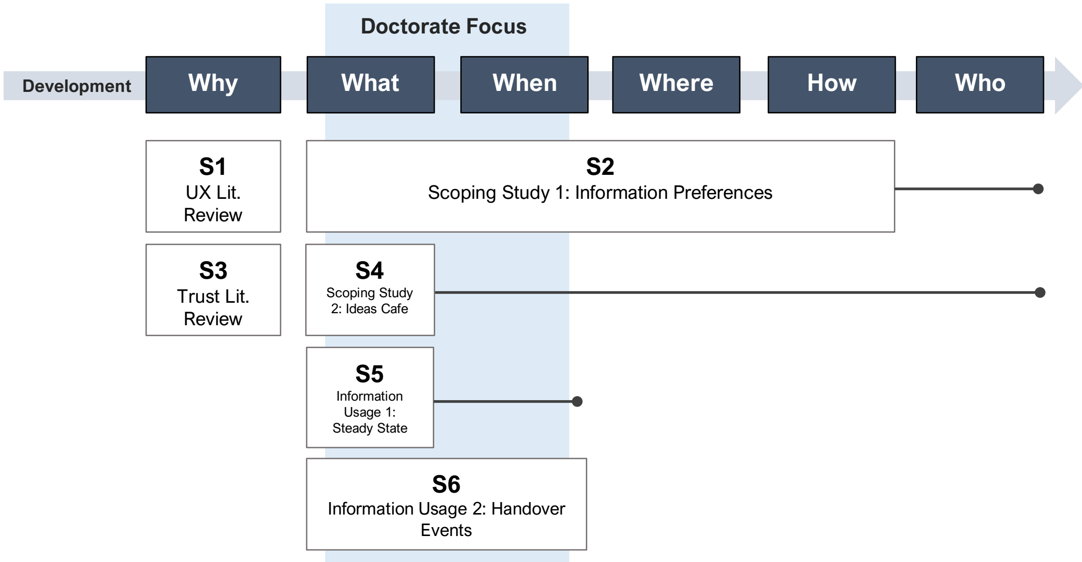


FIGURE 2 DOCTORATE STRUCTURE

Along the top of the diagram above is ‘Development’. Key questions around why, what, when where, how and who must be addressed to design solutions to the HMI challenge in partially automated vehicles. Hence, this arrow represents how the questions should be addressed in their expected chronological order of development. The blue bar titled ‘Doctorate Focus’ represents the questions which this doctorate focused on. The remaining boxes illustrate which questions were addressed by each Submission (S#). The thin black lines that extend from some boxes indicates where the results touched on additional areas but were not the focus of that study.

Submission 1: UX Literature Review and Submission 3: Trust Literature Review, both aimed to develop a more detailed understanding of the problem of HMIs inside partially automated vehicles. Consequently, the need for an investigation into the driver's information preferences was apparent, leading into Submission 2: Interview Study which investigated *what, when, where* and *how* information should be presented. Through thematic analysis, it was found that different types of drivers have different expectations of what a partially automated vehicle was capable of. Consequently, this had an impact on their information preferences to be presented to them inside the vehicle. This was an early indication that failing to account for differing driver expectations can cause problems for the system's use. This led to Submission 4: Ideas Café, where information preferences were explored with a much broader demographic and the concept of trust was explored for the first time in the doctorate. These two scoping studies highlighted the importance of understanding what information drivers require inside partially automated vehicles. Hence Submission 5: Information Usage Study 1 and Submission 6: Information Usage Study 2 moved to focus on this area specifically.

Submission 1: Understanding what the issues are in partially automated HMI

In the first submission, the area of user experience in partially automated vehicles was explored using a literature review. It was the first document in the portfolio that began to answer the questions of *why* this area needed investigation through research. The initial scope of the research was more focussed around the user experience of vehicles and as a result of this literature review, the area of usability was found to be more suited to the goals of the EngD. The submission summarised the many different usability related issues facing partially automated vehicles, such as designing for acceptance, trust, enabling new forms of interaction, as well as maintaining the driver's awareness so they may quickly resume control if and when requested. There was also evidence for the importance of the vehicle to driver communication with the help of information presented inside the vehicle. However, at the time of writing, there was no study that had looked into what information drivers require in a partially automated vehicle. This was the motivation for the following study. There was an opportunity to investigate the information requirements for drivers in a partially automated vehicle and how this may change in different driving scenarios.

Submission 2: Understand what information users need in partially automated vehicles

This qualitative study used the immersive WMG 3xD simulator to present an automated driving scenario to participants and ask what kinds of information they would want the vehicle to present during different scenarios. Interview results were transcribed and coded. Through thematic analysis, two groupings of participants, those with High Information Preferences and those with Low Information Preferences (HIP and LIP), were found. These information preference groupings appeared to originate from the participant's expectations of what a partially automated vehicle should be able to do. This study crucially highlighted how different drivers have different expectations of technology and how this has an impact on their information preferences and the importance of appropriately designing HMIs and showed evidence for the reason current HMIs in partially automated vehicles may not be as effective as they could be. Highlighting these different groups (HIP and LIP), better equips HMI designers to design the communication between the driver and the vehicle, regardless of the driver's predisposition.

Submission 3: Understanding how usability can be enhanced by designing for trust

Trust was raised as a potential explanation for the two groupings of drivers, although it was never explicitly explored in the previous study. The aim of this Submission was to understand aspects of trust, as at the time, it appeared as though the project may move more in the direction of understanding trust. Hence, a literature review was conducted. The goal was to take the understanding from this review into the next study, which was aiming to explore information preferences with a much broader demographic and a more qualitative methodology. This literature review covered the different types of trust and how each can develop. In particular, there was a focus on how trust can be achieved through the design of the internal HMI. The review found several trust models, such as the Trust model by Choi and Ji (2015) that provided an important theoretical backing in the selection of information for the latter eye-tracking studies.

Ultimately, as will be discussed in this Innovation Report, the project moved away from specifically looking at trust, and more towards the practical requirements of understanding information usage inside a vehicle (with an understanding that trust, situational awareness and cognitive workload, were aspects that affected information requirements).

Submission 4: Exploration of usability at a broader and a higher level of autonomy

To further explore information preferences in automated vehicles, a public engagement event was designed using the Ideas Café format. This was a chance to explore information preferences with a broader demographic. The focus on trust resulted from the idea that it may have had an impact on the development of the two driver groupings (HIP and LIP). At this point in the EngD, there was still scope to explore different factors affecting information preferences; hence the event focussed on the development of trust. A number of emergent themes arose from the thematic analysis around Society & Policy, Data & Privacy, Internal HMI and Inclusive Design. Of these emergent themes, the codes regarding Inclusive Design was of most interest to this doctorate, given the focus on the design of HMI. The key was the information presented to the driver in communicating the vehicle's intentions and competence. This was the number one concern for drivers in their development of trust with the vehicle.

It was evident that even at higher levels of vehicle autonomy, the information presented inside the internal HMI still plays an important role. Submission 2 highlighted the importance of the internal HMI from the perspective of user preferences and their expectations of partially automated vehicle capability. Submission 4 then highlighted the importance of the information presented from the perspective of trust. Being able to design an HMI that can appropriately support the driver in the use of the system is an important factor. However, questions remained over understanding what these information requirements are.

Submission 5: Information usage during steady-state driving and how this changes with increasing familiarity in a partially automated vehicle

One of the solutions posed to adapting to different driver predispositions and information preferences is the adaptive HMI; an HMI capable of changing the information it displays to best suit the situation or driver. The changes in information can be accomplished in several ways: based on the driver's workload, preferences, situational awareness or familiarity with the system. The idea of adaptive HMIs has been long suggested, but there had yet to be a study that aimed to define information usage according to the driver's familiarity with the partially automated system.

Submission 5 first began by the development of a shortlist of information that should be presented by the HMI, to begin to define the information requirements for partially automated vehicles quantitatively. This shortlist was developed based on the results from Submission 2: Interview Study and Submission 4: Ideas Café, indicating some of the information that drivers require. Next, this shortlist was refined with collaborative help from experts from industry, eventually resulting in nine types of information that could be presented to the participants. This information could be considered representative of a partially automated vehicle HMI.

This led to the design of a longitudinal within-subjects study. Each participant experienced up to two driving simulations per day for five consecutive days. Participants were advised to be prepared to take over control, but this was never required. The information presented to participants was split into two categories: Technical Competence (regarding the current state of the vehicle) and System Transparency (regarding the future state of the vehicle). These two definitions were based on the Trust Model developed by (Choi & Ji, 2015) The results found that drivers tended to use the information around the technical competence of the system more and information about system transparency less. This confirmed many of the issues currently facing partially automated vehicles today: as drivers become more accustomed to the system, important information about the future state of the vehicle becomes less used. Drivers wanted less information about the specific detail from the vehicle's sensors and more confirmatory information saying everything is working as it should.

With the information usage during steady-state defined, the next step was to understand this during different driving events in order to create a more robust design recommendation.

Submission 6: Information usage during steady-state over time and driving events in a partially automated vehicle

The final study in this doctorate focused on expanding the understanding of information requirements from the previous three studies. The same nine types of information were used again. This time, driving events were introduced to participants. The study design was also shortened to three days but retained the same number of simulation exposures as the previous Submission 5: Information Usage Study 1. The study found that system transparency information was more consistently used when the risk of handover appeared to be higher. In Information

Usage Study 1, participants were advised to be ready to take over control, but this was never required. In this Submission 6: Information Usage Study 2, the handover events may have meant that participants were more alert and ready to use future state information. The study found that after all events (handovers and warnings), the use of Action Explanation always increased. This was a significant result as comparable information, that could explain what the vehicle was doing and why, was not observed on any existing HMI. Using this post-event and steady-state (all exposure before a driving event occurred) from Submission 6: Information Usage Study 2, the steady-state results from Submission 5: Information Usage Study 1 and the results from the first two scoping studies, a set of design recommendations were then made. These design recommendations can be applied to the design of a future adaptive HMI.

1.4. Structure of this report

This report will now present the findings from each of these submissions (Table 1). For clarity, each submission has been given a name that better describes its contents.

TABLE 1 STRUCTURE OF THIS REPORT

Section	Submission	Description
1 Introduction	-	Introduces the challenges facing HMI in Level 2 partially automated vehicles (and above) and presents the aims, objectives and structure of this Innovation Report.
2 What are the HMI challenges facing partially automated vehicles?	1, 3	Presents a more detailed review of the three challenges facing HMI in partially automated vehicles: trust, cognitive workload and situational awareness.
3 Methodology	All	Presents the rationale for the use of the methodologies in this doctorate's studies.
4 Scoping Study 1: Information Preferences	2	Presents results from Submission 2, an interview study into information preferences in partially automated vehicles.
5 Scoping Study 2: Ideas Café	4	Presents results from Submission 4, a public engagement event using the Ideas Café methodology.
6 Adaptive HMIs as a Solution	5	Presents relevant literature that bridges the two Scoping Studies with the two quantitative Information Usage Studies.
7 Information Usage 1: Steady-State [IUS1]	5	Presents the results from Submission 5, an eye-tracking study that aimed to classify information usage during steady-state driving using a longitudinal study design.
8 Information Usage 2: Handover Events [IUS2]	6	Presents the results from Submission 6, another longitudinal eye-tracking study that aimed to classify information usage in a partially automated system where the participant was required to react to handover and warning events.
9 Design Recommendations	-	Presents a synthesis of the results from all four studies to provide design recommendations around the information required for future partially automated vehicles.
10 Research Impact	-	Discusses the research impact of the work from the perspectives of academia, for the sponsoring company, Jaguar Land Rover and the wider industry.
11 Conclusion	-	Concludes this Innovation Report with remarks around the essential findings and contributions of this work.

From this point, for clarity, this report will refer to the four studies in this doctorate by their Section titles rather than their submission numbers.

2. What are the HMI challenges facing partially automated vehicles?

The SAE defines Level 2 partially automated driving as:

> *"The sustained and ODD* [Operational Design Domain]*-specific execution by a driving automation system of both the lateral and longitudinal vehicle motion control subtasks of the DDT* [Dynamic Driving Task] *with the expectation that the driver completes the OEDR* [Object Event Detection and Response] *subtask and supervises the driving automation system"* (SAE, 2018)

The definition above makes a clear statement that the human driver must be ready to respond to a handover request from the vehicle at any time, and this is where much of the challenge of designing HMIs for partially automated vehicles is focussed. It is around keeping the driver appropriately aware of the vehicle's intentions and driving condition, so that they may be able to safely take back control when required or intervene sooner in an emergency scenario.

Evidently, there are numerous usability challenges that need to be solved for partially automated vehicles, including handover (Morgan et al., 2019; Walch et al., 2015), cognitive workload (Khastgir et al., 2018b; Stapel et al., 2019) and trust (Kohn et al., 2018; Molnar et al., 2018). For example, by definition, handover at Level 2 can be unpredictable, requiring the driver to take control of the vehicle at short notice quickly. To be able to facilitate such a handover request at short notice, the driver must be situationally aware of their surroundings, adding to the cognitive workload. In effect, these partially automated systems are asking drivers to take on a new role, as monitors of the automated process.

Outside of the automotive context, it has been demonstrated that the co-operative relationship between the human and the system is crucial to ensuring the safe usage of the system (Bowen, 2008; Wessel et al., 2019). For example, tragic incidents such as fatal aeronautical crashes like the Air France 447 and Aeroflot Flight 593 have been attributed to a number of issues that affected the co-operative relationship between the pilot and the system; such as inadequate communication from the HMI (Wessel et al., 2019). Despite these fatal incidents, the vast majority of flights operate with no issues (CAA UK, 2013). Contexts such as aeronautics have the benefit of operators and pilots who have been trained for multiple years to appropriately use automated systems and how to respond in situations where the automation may fail. This is not the case in automotive vehicles, where the use of automated systems is not yet included in driving licence training. In vehicles today, older drivers can experience difficulties with the use of Advanced Driving Assistance Systems (ADAS) (Bellet et al., 2018). There are questions around whether drivers will need to be 'recertified' for the use of partially automated vehicles (Holstein et al., 2018).

The situation is further complicated by the varying definitions of autonomy from different manufacturers. For example, Audi claims to have Level 3 technology, but the system is limited to only traffic jam speeds up to 37mph (de Prez, 2018). According to the SAE definitions, Level 3 should be capable of all aspects of the DDT in a limited ODD and should only require intervention when the system requests. That is to say, the system is fully capable when it is within its ODD and does not require the driver to monitor its operation unless it explicitly requests a handover. Similarly, Tesla's Autopilot system can provide automated driving on motorways, with lateral and longitudinal control with lane changing. However, some features are geographically restricted and Tesla have had troubles with the name 'Autopilot' implying a higher capability than is currently possible (ETSC, 2016). Tesla's system has been classified as a Level 2 system (Banks, Plant, et al., 2018), despite offering greater flexibility and capability than Audi's system. It is becoming increasingly evident that the definitions provided by the SAE have limitations and the technology deployed by automotive manufacturers appear to blur the lines between the levels.

These concerns around the safety implications of automated vehicles is a common motivation for studying this area. There has been a demonstrable negative impact on driving behaviour after the vehicle hands back control, with longer reaction times and the risk of excessive trust in the automated system (Brandenburg & Skottke, 2014; Merat & Jamson, 2009). For example, these studies found that drivers drove with a significantly reduced distance to the lead vehicle after being handed control of the vehicle from automated driving and that reaction times to critical driving events had increased significantly by approximately 78%.

Three key areas have been identified that contribute to the challenge of designing for partially automated vehicle HMIs: cognitive workload, trust and situational awareness (Chen & Barnes, 2014; Raja Parasuraman et al., 2008). These have been shown diagrammatically below in Figure 3.

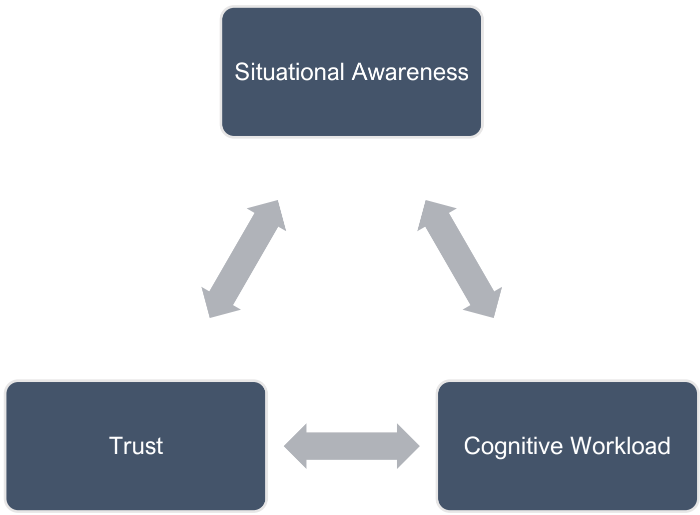


FIGURE 3 THREE CHALLENGES FOR FUTURE HMI (CHEN & BARNES, 2014; RAJA PARASURAMAN ET AL., 2008)

This section will now present each of these three in detail. However, as the review of the literature found, each of these three challenges is complex, with interactions to factors beyond just the HMI inside the vehicle.

2.1. Three key challenges for future HMI

2.1.1. Implications of Cognitive Workload and Situational Awareness

From a broader cognitive workload perspective, monitoring any automated process has been shown to increase the cognitive workload on the operator (Kaber & Endsley, 2004; Sheridan, 1995). Consequently, these papers suggest that this increased cognitive workload can cause drivers to fatigue and disengage with the task; meaning they fail to maintain an appropriate level of situational awareness.

For example, use of frameworks such as Event Analysis of Systematic Teamwork (EAST) has allowed the diagrammatic representations of the increased cognitive complexity of using an automated vehicle (Banks & Stanton, 2019; Griffin et al., 2010; G. H. Walker et al., 2010). These studies have found that the cognitive processes involved in partially automated vehicles were denser and more complex than those of manual driving. The evidence would strongly suggest that this is a result of the driver being placed in the monitor role and having to be responsible for knowing the aspects of the driving task have been automated, as well as the corresponding limitations and capabilities (Hoc et al., 2009; Sarter, 2007; G. H. Walker et al., 2001). Experimentally, this has been demonstrated by studies that have found the quality of driving decreases (Gold et al., 2013), sometimes for up to 40 seconds after handover (Merat et al., 2014). For example, one of the most common consequences is mode confusion, where the driver performs an incorrect action because of uncertainty around the capability of the automated system (Endsley, 2017; S. H. Lee et al., 2014; Shaikh & Krishnan, 2012). These findings have been illustrated by (Banks & Stanton, 2019) (Figure 4), who highlight the difficulty of a distracted driver having to move directly to a driving role during a handover of control.

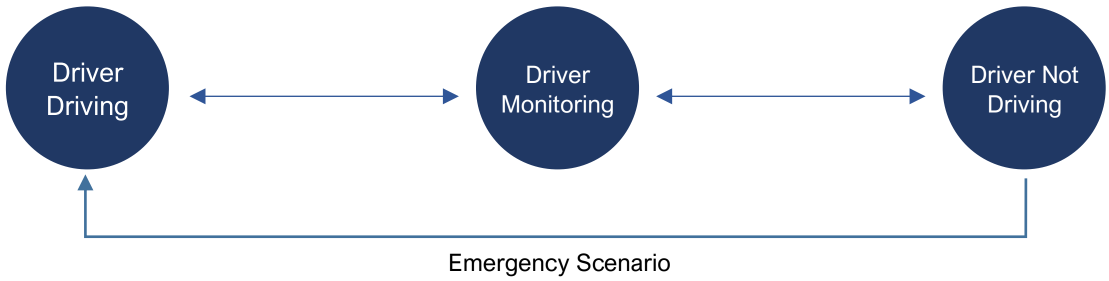


FIGURE 4 COGNITIVE PROCESSES DURING AUTOMATED DRIVING. ADAPTED FROM (BANKS & STANTON, 2019)

One of the earliest theoretical representations of this reduction in performance as a result of cognitive workload was the Yerkes Dodson curve (Yerkes & Dodson, 1908) represented below in Figure 5. The graph suggests that a person who has either a very low or very high level of arousal (cognitive workload) will have impaired performance in the task they are performing. In other words, there needs to be a moderate level of stress placed on the driver in order to ensure optimal performance.

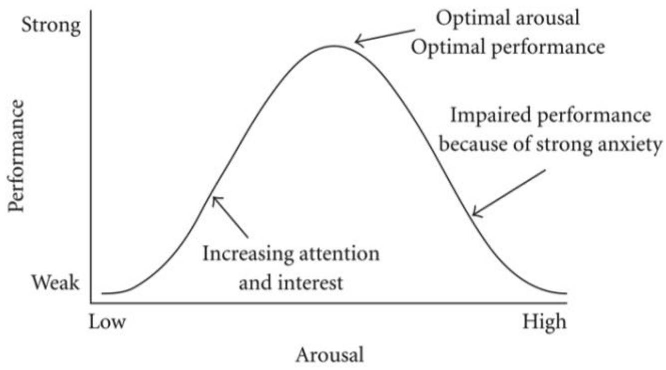


FIGURE 5 YERKES DODSON CURVE (YERKES & DODSON, 1908)

In recent years, this theory has been tested and shown to be still true with interactions between drivers and partially automated vehicles (Coughlin et al., 2011; Feldhütter et al., 2019; Ko & Ji, 2018; Miller et al., 2015; Strayer & Fisher, 2016). When arousal was reduced, delayed reaction times have been observed for the driver to take back control from the vehicle (Naujoks et al., 2016) and low arousal has been attributed as a key reason why drivers disabled automated driving altogether; to avoid the onset of sleepiness and boredom (Van Huysduynen et al., 2018). Moreover, several studies commented that different participants had different impacts on their workload from the same simulated conditions and tasks (Feldhütter et al., 2019; Naujoks et al., 2016; Strayer & Fisher, 2016); indicating that a driver's performance in a partially automated vehicle is a complex construct that varies between individuals.

2.1.2. Implications of Trust

Trust plays an important role in the development of the relationship between humans and automated systems (Carter & Bélanger, 2005; Choi & Ji, 2015; J. D. Lee & See, 2004; Raja Parasuraman et al., 2008). This is because the use of an automated system will inevitably require humans to relinquish control of the task to the system and to trust the system will be able to do the task successfully. Beyond just the automotive context, trust is crucial to the acceptance and use of new technology (Carter & Bélanger, 2005; Gefen et al., 2003; Pavlou, 2003). The formation of trust with automated systems depends on several discrete but interacting variables. These variables have been given a number of different labels and the number of variables vary between the different models of trust (Choi & Ji, 2015; Hasan et al., 2012; Hoffman et al., 2013; Jian et al., 2000; Mayer et al., 1995; Mcknight et al., 2011; Schaefer et al., 2016). For example, McKnight et al. (2011) highlight reliability, functionality and helpfulness as their factors of trust. In comparison, Choi and Ji (2015) highlight system transparency, technical competence and situation management as the key factors for trust development. Hoffman et al. (2013) highlight four factors: reliability, validity, utility, robustness and the false-alarm rate. There is little consensus on the labels given to the factors of trust or even how many there should be.

The challenge for the HMI of a partially automated vehicle is to present the appropriate information, to improve the usability and user experience of the system and consequently help foster trust and acceptance. However, the relative impacts of the categories of functionality, utility and predictability on trust are not equal. There is evidence to suggest that presenting information on 'why' the vehicle is following a set of actions (functionality) led to better performance when taking back control from the system than information on what the vehicle was about to do (predictability) (Beller et al., 2013; Helldin et al., 2013; Koo et al., 2015). Koo et al. (2015) noted that the best handover performance came from presenting both sets of information (on functionality and predictability), but this was the least preferred by participants, and this may increase the number of incorrect responses to information presented during automated driving (R. Parasuraman et al., 2000).

There is then the question of how much trust should a user have in the system. An important concept in the development of trust is the 'calibration' of trust, the idea that both too little and too much trust has a negative effect on the driver's use of the automated system (Gefen et al., 2003; Pavlou, 2003). The calibration of trust is defined as "*the correspondence between the person's trust in the agent and the agent's capabilities*" (J. D. Lee & See, 2004, p. 55). There is a consensus that over trusting a partially automated vehicle will degrade human performance, with glances to the roadway decreasing significantly (Hergeth et al., 2016; Körber et al., 2018; F. Walker et al., 2018) resulting in significantly decreased in situational awareness (Morgan et al., 2019). Outside of the driving context, over-trust (or complacency) has been attributed as a contributing factor in several aviation accidents (Wickens, 1995), for example in the over-reliance on information provided by automated support systems (Mosier et al., 1994).

Up to this point, the development of trust has been considered, but trust itself has different forms. Submission 3 explored in detail the definition of trust as well as the different forms of trust. Specifically, trust as an entity that develops over time through accumulating experiences both in the present and the past (Azzedin & Maheswaran, 2002; Fullam & Barber, 2007; Teacy et al., 2006). These are represented in the different forms of trust: dispositional (the stable initial propensity to trust), situational (more transient and dependant on the situation) and learned (the dynamic development over time) (Schaefer et al., 2016). According to these definitions of trust, it is only situational and learned trust that can be influenced through the design of the vehicle's HMI (as dispositional is an inherent characteristic of the user). Moreover, the importance of trust is well understood. It is often recognised as one of the key factors in the acceptance and adoption of new technology and services (Flynn et al., 1994; Siegrist, 2000; Zhang et al., 2019) and the HMI presented to the driver inside the vehicle is the chance for their situational and learned trust to be influenced and developed appropriately (Wei et al., 2013).

2.1.3. Summary

It is evident that all three of the constructs of trust, situational awareness and cognitive workload play a role in the usage of a system. While the individual constructs could be explored independently, the view taken in this project was to consider them holistically and look at the resulting impact on the usage of the HMI. Consequently, Driver Behaviour Models were then considered to understand how previous authors had assimilated the various constructs of human behaviour into models that could then be applied to the design of an interface.

2.2. Driver Behaviour Models

The implications of situational awareness, cognitive workload and trust have been discussed in relation to the challenges for HMI design in automated vehicles. In response to these implications, driver behaviour models have been developed to try to describe and categorise the impact of these issues.

2.2.1. Primary, Secondary, Tertiary (1985) (Situational Awareness)

In order to address the challenge of prioritising information so that the most important information is placed in the most pertinent locations in front of the driver, Geiser (1985) proposed the Primary, Secondary, Tertiary model of information categorisation (Geiser, 1985). The model has been used across a range of different HMI research (Döring et al., 2011; Tönnis & Klinker, 2006). Information can be categorised into the three categories:

- **Primary** tasks are those relating to the control of the vehicle. This would include information that assists the driver in manoeuvring the vehicle itself, or to understand the automated vehicle's intent.
- **Secondary** tasks are those relating to increasing the safety of the vehicle for the driver as well as other roads users and the environment. This would include information that assists the driver in driving safely or enables them to understand the situation around the vehicle so you can take over control safely if need be.
- **Tertiary** tasks and information are those related to the information systems in the vehicle, or entertainment. Often, tertiary tasks are those considered a 'luxury' with respect to the driving task, though often they are highly desirable for drivers of modern vehicles

2.2.2. Skills, Rules, Knowledge by Rasmussen (1983) (Cognitive Workload)

The individuality of how different people act on information and perform actions was illustrated by Rasmussen's (1983) Skills Rules Knowledge model (thereinafter SRK) (Rasmussen, 1983). The model posits that behaviour can be categorised into either skill, rule or knowledge-based action according to their cognitive demand and (more recently) the uncertainty of the operating environment (Cummings, 2018) (Figure 6). Further, the model should be considered as a continuous spectrum between levels, as opposed to three discrete categories (Halbrügge, 2018; Kirwan, 2017; K. J. Vicente & Rasmussen, 1988).

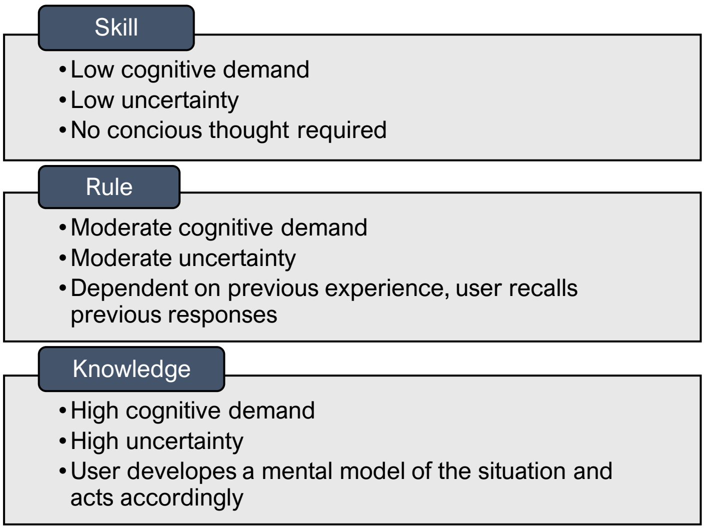


FIGURE 6 SKILLS, RULES, KNOWLEDGE MODEL (RASMUSSEN, 1983)

There have been suggestions that this should become an industry-standard in the design of HMIs (Cummings, 2018; Harwood & Sanderson, 1986). Given that the balance of workload is so crucial to the ability of the driver to use a partially automated vehicle and that different drivers have different reactions concerning their cognitive workload, the role of the HMI in supporting the driver becomes increasingly important and more challenging to design.

The levels of the SRK may be used to help guide the design of HMIs in partially automated vehicles. Considering the Yerkes-Dodson curve, this would suggest that skill-based behaviour may not stimulate enough cognitive workload for optimal performance, while knowledge-based behaviour would be considered too mentally demanding. Though there are differing opinions on this, with some arguing that automatic, skill-based behaviour is more likely to be riskier and more error-prone (Hobbs & Williamson, 2002; Salminen & Tallberg, 1996). Conversely, others have argued that those errors originating from skill-based behaviour are the least common (Runciman et al., 1993; Wiegmann & Shappell, 1997) and that rule-based errors were the most common (Shryane et al., 1998).

While there may be no clear consensus as to what type of actions are more error-prone, it is evident that there is a dearth of understanding of how drivers move between the different levels of the SRK (Figure 6) in a partially automated vehicle. For instance, it had yet to be investigated what information drivers require when in different driving conditions. From the definitions provided by Rasmussen (1983) and Cummings (2018), new drivers of partially automated vehicles will likely be relying on knowledge-based behaviour, as evidenced by the increased cognitive demand observed (Griffin et al., 2010; G. H. Walker et al., 2010). However, as a driver becomes more accustomed to the vehicle, cognitive 'shortcuts' can likely be identified and behaviour moves more towards the rule and skill-based levels (Halbrügge, 2018; Hollnagel, 1998). Hence, it is unknown how the HMI should best support this transition.

It has been demonstrated how the workload can harm the relationship between the human driver and the automated system. This consequently has an impact on the driver's situational awareness, negatively effecting the usability and user experience of the vehicle. This was shown to be valid for both under- and overloading of the driver with information and cognitive effort. The remaining factor in the challenge of designing HMIs for partially automated vehicles is trust.

2.2.3. Trust Model (Choi & Ji, 2005) (Trust)

Representing the trust aspects of the HMI challenges, is the Trust Model (TM) by Choi & Ji (2015). Three components of trust were highlighted by the model: System Transparency, Technical Competence and Situation Management.

- **System Transparency** describes the system's ability to communicate with the driver so they may predict and understand the operation and capabilities of the automated system (Choi & Ji, 2015). This is attributed to information that assist the driver in creating a mental model of the vehicle's operation (Kieras & Bovair, 1984), which is also consistent with the SRK model (Rasmussen, 1983).
- **Technical Competence** describes the driver's perception and expectation of the performance, shown to be critical in the development of trust (Maltz et al., 2004; Moray et al., 2000).
- **Situation Management** is how easily the driver believes they are able to take over control from the system (Choi & Ji, 2015).

These three aspects contribute to the development of a user's trust in a system. The model has limitations in that the development of the model may have been limited by the demographics that were included in its creation. However, the model has been accepted as a valid interpretation of the constructs of trust (J. Lee et al., 2019; Zhang et al., 2019), given that it was developed on the basis of the well-established Technology Acceptance Model (TAM) (Scherer et al., 2019).

2.3. How can these challenges be addressed?

Situational awareness, cognitive workload and trust are all interrelated in a complex relationship. The importance of effective communication between the vehicle and the driver has been highlighted previously in this Section as a method of addressing all three of the challenges discussed (Bowen, 2008; Choi & Ji, 2015; Wessel et al., 2019).

The goal of the HMI must be to provide enough context and information to the driver to maintain their situational awareness, without cognitively overloading them (Umeno et al., 2018), enabling them to maintain an appropriate trust level and hence improve the usability of a future partially automated vehicle. This sequence of factors begins with the information presented to the driver. This information is key in the development of the mental models that enable the driver to act as a monitor of the automated process (Blömacher et al., 2018) and has an effect on the situational awareness, cognitive workload and trust.

For example, presenting information on system transparency (what the vehicle understands from its sensors about its environment), increases the driver's situational awareness and consequently important in the development of trust (Lyons et al., 2017). Jung et al.'s (2015) study on displaying uncertainty indicators to drivers found that anxiety was lowered and trust was maintained at an appropriate level even under challenging scenarios for the simulated automated system (Jung et al., 2015). This was consistent with results from Dzindolet et al. (2003) who found that background information and providing rationale on the system increased trust (Dzindolet et al., 2003).

This would suggest that providing the driver with as much information as possible is the optimal solution for trust and situational awareness, however, this then negatively impacts the cognitive workload. For fighter pilots, it was found that providing more detailed information resulted in more correct decisions being made in the use of the automated tool, but a higher cognitive workload and slower decision time (Helldin et al., 2014). This effect has been observed before, that providing too much information means it is likely that much information won't be processed and cognitively understood (Clark et al., 2018). For example, Clark, Stanton and Revell (2008) found that participants thought that presenting too much information was inefficient to the detriment of the HMI design. Hence, rather than providing a lot of information continuously, it has been suggested that providing a more straightforward HMI with only the most crucial and concisely presented information be used (Clark et al., 2018; Kraft et al., 2018). In Kraft et al.'s (2018) study, they found that glances to the driving task increased significantly when a 'reduced' HMI (confirming the vehicle's operation) was presented to users compared to a 'full' HMI (detailed information on lane position).

In partially automated vehicles today, despite the research strongly suggesting the contrary, the approach has been to provide the driver with as much information as possible in the hope that some of the information will be processed and keep the driver situationally aware (P. Olsen, 2018). The effects of cognitive overload and the consequent disengagement with the monitoring task required that have been discussed theoretically in the literature, have all been observed in real-world driving conditions today (Lyu et al., 2017; Manawadu et al., 2018; Merat et al., 2014).

To design an HMI that can support the driver in the development of their situational awareness, manage their cognitive workload and calibrate their trust level is the goal and must be understood.

This doctorate aimed to understand how HMIs can more appropriately support the driver in the use of a partially automated Level 2 vehicle system or higher. The aim represents a difficult challenge, and the following research first set out to explore the topic in a broad sense, understanding what areas of the HMI need further research. What follows are two scoping studies that attempted to capture the critical requirements in this area to inform the latter, more quantitative studies. The next section will describe the methodologies used that were common across multiple studies in this doctorate.

3. Methodology

This doctorate aimed to understand how HMIs can more appropriately support the driver in the use of a partially automated Level 2 vehicle system or higher. A range of different methodologies were deployed, using both qualitative and quantitative methods to answer this question.

The previous section has covered the *why* is the information currently presented in partially automated vehicles a problem? With the numerous challenges facing users of partially automated vehicles being explored in detail. The key challenge is maintaining the driver's situation awareness despite them being placed in a supervisory monitoring role that is known to be difficult for humans.

The remaining questions concern *who* the users of partially automated vehicles are? *What* information do they require? *When* should this information be presented? *Where* should this information be presented and *how*? The submissions in this doctorate contribute to all the questions in this structure in varying degrees. It became evident that there was a lack of research on the questions of *what* information drivers use in partially automated vehicles; hence the doctorate quickly focussed on the question of *what* and *when*.

In answering these questions, a range of different methodologies was employed, requiring the use of both qualitative and quantitative methods of data collection.

3.1. WMG Driving Simulators

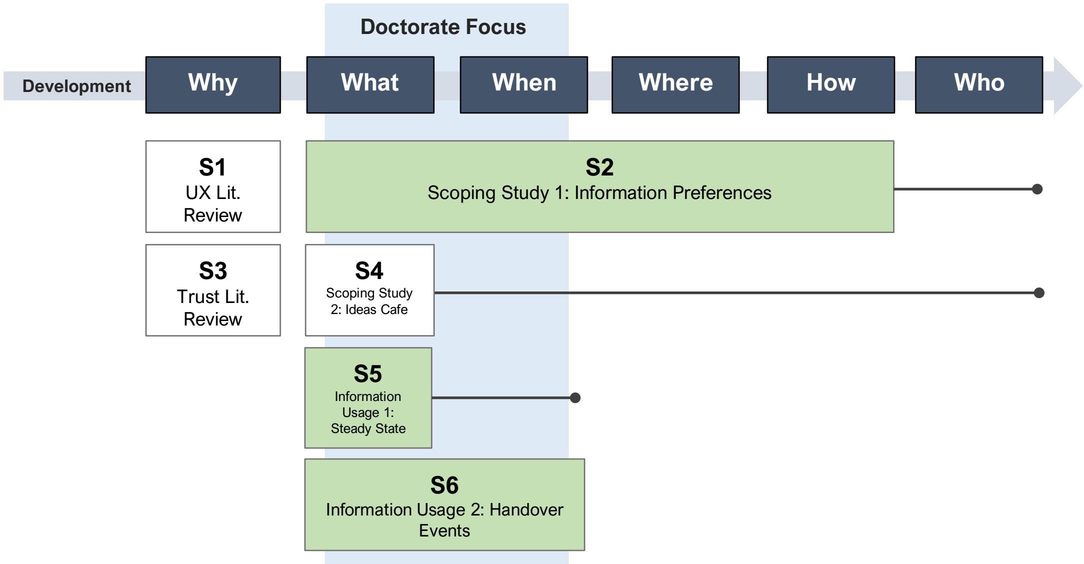


FIGURE 7 DOCTORATE OVERVIEW. SUBMISSIONS USING SIMULATORS ARE HIGHLIGHTED

Three of the four studies in this doctorate (except Scoping Study 2: Ideas Café) used the driving simulators available at WMG, University of Warwick (Figure 7).

The WMG 3xD Simulator (3xD) is an immersive driving simulator situated at the IMC Building, WMG (shown below in Figure 8). The 3xD features six projected screens in a 360° formation. At the centre is a Range Rover Evoque Built-Up Cab (BUC). The BUC's hardware (such as steering wheel and pedals) connects to the simulator, enabling an immersive experience for participants. The 3xD is housed in inside a Faraday cage; allowing for a quiet environment, free from distractions for participants. All scenarios are controlled from the control room adjacent the simulator room.

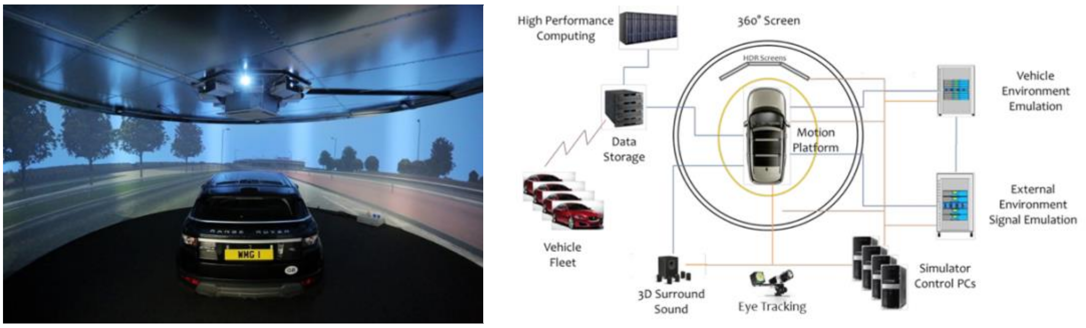


FIGURE 8 WMG 3XD SIMULATOR. PHOTO (LEFT) AND SCHEMATIC (RIGHT)

The WMG Development Simulator (Dev Sim) features identical software capabilities but presents scenarios on three large screens around a gaming race chair, steering wheel and pedals (shown below in Figure 9). The Dev Sim offers greater accessibility to the simulator hardware, enabling easier development of scenarios as the researcher can move between the simulator and the development PCs quickly during testing and experimentation. The Dev Sim was situated inside a sound lab room that was booked for private, uninterrupted use.

There are two options for the development of driving scenarios for both simulators; both were used in this doctorate. One uses LIDAR scanned imagery from around the Coventry area, featuring 1:1 replications of the real world roads. This can help participants increase their immersion by seeing locations they are familiar with. However, loading times are notably longer when opening a scenario. Consequently, this required extra consideration when planning the length of a study session.

Alternatively, scenarios worlds can also be custom built. This enables the creation of road layouts and situations exactly as required by the study. Custom worlds are visually identical to the LIDAR scanned imagery, with a comparable range of road layouts (motorways, rural, urban and village) available for selection. Customer worlds load notably faster compared to LIDAR scanned imagery, enabling greater flexibility during participant study sessions. In this doctorate, Scoping Study 1: Information Preferences presented simulations using the LIDAR scanned imagery. Information Usage Studies 1 & 2 both used custom worlds.

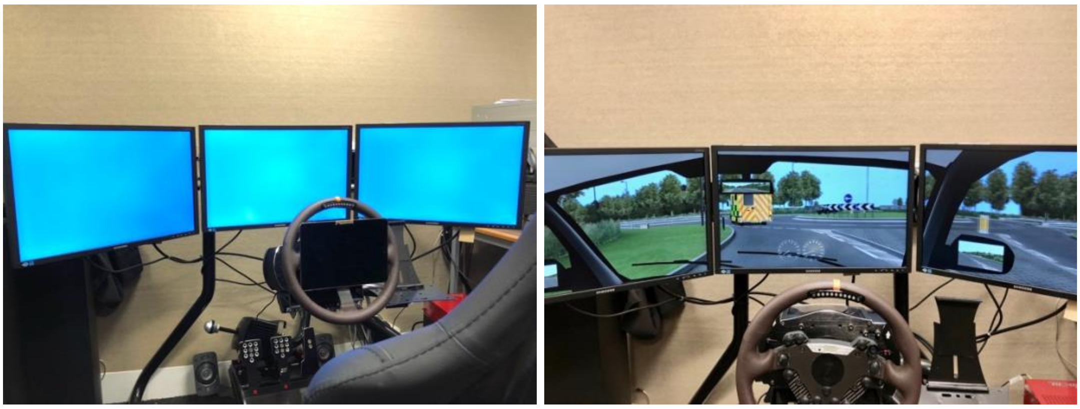


FIGURE 9 WMG DEVELOPMENT SIMULATOR. ON STANDBY (LEFT) AND DURING A SIMULATION (RIGHT)

Driving simulators are becoming increasingly popular in the testing and validation of many aspects of vehicle research, for example, in the investigation of motion sickness (Brooks et al., 2010), in the development of city models (Grasso et al., 2010) and for evaluating trust (Khastgir et al., 2017). Their popularity can be attributed to the flexibility they offer in terms of scenario design. Many different driving conditions and environments can be tested in a single location with no crash or safety risk to the participant (Brooks et al., 2010). Experimentally, driving simulators offer a repeatable environment, necessary for the validity of results (Classen et al., 2011; Reed & Green, 1999). With particular consideration to automated vehicles, this is currently very difficult to test as automated vehicles are not readily available.

Further, legislative and ethical challenges make testing automated vehicles on public roads prohibitive in comparison to a simulated environment. Many of the scenarios that would need to be tested for (such as in the event of a near accident) would not be safe to test. The simulated 3xD and Dev Sim environments allow for the safe and convenient testing of many different driving scenarios.

3.1.1. Simulator Validity and Transferability of Results

Transferability from simulator results to the real world is a key question (Caird & Horrey, 2011) and simulator validity has been evaluated in two ways. Either, by considering the vehicle's physical response i.e. how well it is able to replicate the experience of driving in a real car (Greenberg & Blommer, 2011); or the behavioural response i.e. how comparable a driver's response to driving events are to real world reactions (Meuleners & Fraser, 2015; Risto & Martens, 2014; Shechtman et al., 2009).

Physical validity has been attributed to good visuals and audio, accurate vehicle motion replication and the tactility of the simulator (Kemeny, 1999). Both the 3xD and Dev Sim provide high fidelity visuals and audio with a motion base. While the 3xD's Range Rover BUC provides a relatively more tactile and realistic environment in comparison to the gaming chair in the Dev Sim, the tactile feel of the seat, steering wheel and gearbox contribute to an immersive experience in both simulators.

Behavioural validity is more complicated and concern two aspects: absolute and relative validity. Absolute validity refers to how close measured values in a driving simulator are to real world driving. Typically, this is difficult to prove because of individual differences in drivers and challenges in replicating the same repeatable conditions in both the real world and simulation (Caird & Horrey, 2011). In comparison, relative validity looks at the relative differences and changes in values, rather than their absolute values, and driving simulators have been proven to provide transferability in this regard (Godley et al., 2002; Törnros, 1998). These studies have concluded that driving simulators do provide an accurate platform in comparison to the real world, by comparing similarities of driving errors in both the real world and in a simulation. They found that across a range of different measures, such as mirror usage, headway choice and speed that there were no significant differences between a simulator and a real-world trial. For example, if a study was to measure the number of fixations to a particular piece of information, while the absolute number of fixations may differ between the real world and simulated environment, the relative differences and changes in usage should be analogous.

The aim of this project was to contribute to the first steps in understanding how future HMI can more appropriately support the driver in the use of a partially automated system, these studies would suggest that the 3xD and Dev Sim provide a justified basis to gain this fundamental knowledge. From both an academic and industrial perspective, it is important that when testing and measure fundamental knowledge, that these first steps are taken in a safe and repeatable environment. What must follow based on these simulator results is a cautious transition to then testing in the real world, before a finalised understanding can be gained.

3.2. Qualitative Methodologies

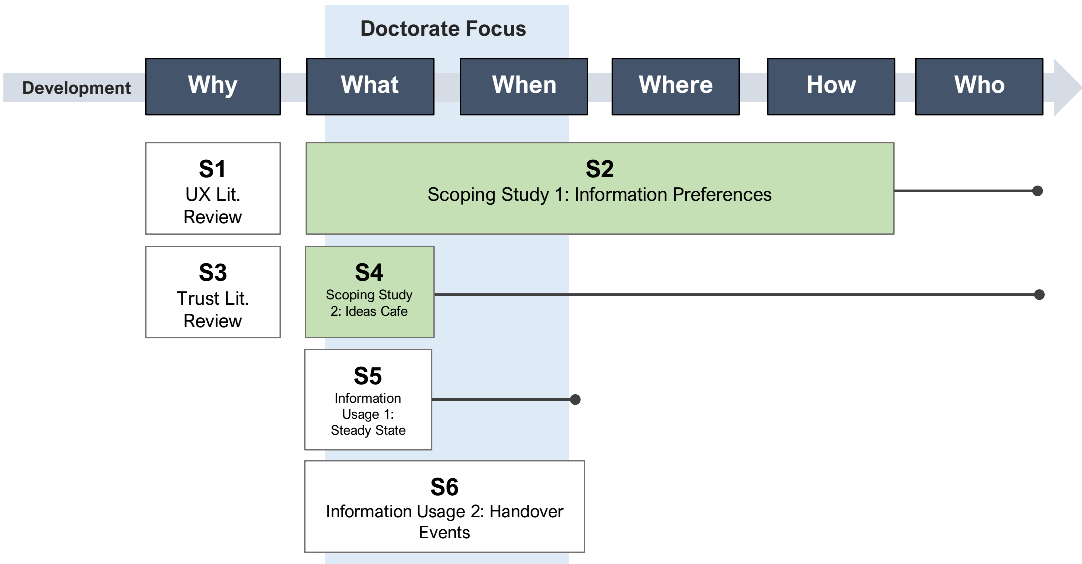


FIGURE 10 DOCTORATE OVERVIEW. SUBMISSIONS USING QUALITATIVE METHODS ARE HIGHLIGHTED

Qualitative methods were utilised in both Scoping Study 1: Information Preferences and Scoping Study 2: Ideas Café, as shown above in Figure 10. Qualitative data can explore the complexities of preferences and behaviours in more detail than is typically possible with quantitative measures (Ivey, 2012; Johnson & Waterfield, 2004). The aim with qualitative methods is to understand, rather than measure, and start from a perspective of discovery rather than the testing of a hypothesis (Forman et al., 2008); avoiding being restricted to the variables selected for experimentation (Patton, 2014). As Figure 10 illustrates, the variables to be tested had yet to be defined and for this reason, adopting a more open-ended, exploratory approach for the initial Scoping Studies was deemed the most appropriate.

Within qualitative methods, there are different methodological options such as focus groups, Ideas Cafés and interviews. Focus groups and interviews are the most common qualitative methods (Gill et al., 2008). This doctorate made use of semi-structured interviews for Submission 2: Interview Study and the Ideas Café format for Submission 4: Ideas Café respectively.

3.2.1. Semi-Structured Interviews (Scoping Study 1: Information Preferences)

> *"Interviewers are not losing their objectivity, becoming partial or imposing a particular world view on the respondent, rather they are using the interview as an opportunity to explore the subjective values, beliefs and thoughts of the individual respondent"* (Davidson & Layder, 1994, p. 125)

For Scoping Study 1: Information Preferences, the interview format was most suited for several reasons. Firstly, the structure of the research (Figure 10) lent itself to an interview format, where each of the questions identified (what, when, where and how) could be explored in detail. Secondly, with only one seat inside the BUC from which the simulator is designed to be viewed from (without causing perspective issues), other qualitative methods such as focus groups would have been infeasible, given that around 3 to 14 participants are required for focus groups (Bloor et al., 2012).

Semi-structured interviews allow for effective exploration of perceptions that methods such as Likert scale questionnaires and structured interview formats may struggle to achieve (Aira et al., 2003; Bryman et al., 1988; Louise Barriball & While, 1994). Ultimately, the format was well suited to the aims of Scoping Study 1, allowing participants to freely express their opinions while also allowing the researcher to follow up on participant remarks outside of the remit of the interview schedule. As with all qualitative techniques, the quality of the analysis is crucial in ensuring valid, non-biased results. This will be discussed in more detail in section 3.2.3.

3.2.2. Ideas Café (Scoping Study 2: Ideas Café)

Scoping Study 2: Ideas Café aimed to understand the factors that affect trust in partially to fully automated vehicles. An opportune public engagement event, organised by the Experiential Engineering department at WMG, was an opportunity to engage with a large number of participants from a broader demographic than the previous Scoping Study 1: Information Preferences.

Public engagement events enable the use of qualitative methods on a broader scale, typically engaging with a large number of attendees for a few hours to discuss a particular topic. The goal is to gather a broad range of opinions in a relatively short period. The value of such events is recognised and there is an increasing focus on formalising the framework for consistency (Ebdon & Franklin, 2006; Yang & Pandey, 2011) as it is increasing in popularity as a decision-making tool (Irwin, 2017; Joss & Bellucci, 2002). These characteristics made the event an ideal opportunity to explore the topic of automated vehicles on a broader scale.

An important aspect of public engagement events is to recognise the opportunity for not only researchers to be informed by attendees, but also for the attendees to be educated (Rowe & Frewer, 2005). Scoping Study 2: Ideas Café, used two distinct methods (table discussions and spectrum lines) designed to assist in the process of designing public engagement events, one of these was the Ideas Café format. However, it was evident that though they used different terminology, there was a consensus across them as to what constitutes the success factors for an Ideas Café, which was summarised below in Table 2.

TABLE 2 COMPARISON OF DIFFERENT MODELS OF PUBLIC ENGAGEMENT SUCCESS FACTORS

Three success factors for Ideas Cafes (Rowe & Frewer, 2005)	**Key Principles of an Ideas Café** (Brown & Isaacs, 2002)	**KCP Model** (Berthet et al., 2016)
Communication	Set the context	Knowledge
Consultation	Create a hospitable space	Conceptualise
	Explore questions that matter	
	Encourage everyone's contribution	
	Cross-pollinate and connect diverse perspectives	
	Listen together for patterns, insights and deeper questions	
Participation	Harvest and share collective discoveries	Proposal

This summarising table became the base on which the Ideas Café was developed. Scoping Study 2 covers in detail how each of the different aspects were achieved, but these will be summarised in the following section.

3.2.3. Qualitative Data Analysis (Scoping Studies 1 & 2)

The same analytical approach was taken for both Scoping Studies, using thematic analysis to understand the themes within participant responses. The thematic analysis approach is commonly used in research to develop theories and meaning from qualitative data (Saldaña, 2013). A coding strategy was created that could be consistently applied to qualitative data gathered. The goal of applying a consistent methodology to the data analysis was to remove the risk of bias in the results and to have a repeatable and documented process.

The analysis began by creating 'codes', which is a word or short phrase that captures the meaning of the participant response and forms the first stage of developing a theory from the data (Maher et al., 2018; Saldaña, 2013; Stuckey, 2015). The first coding method was descriptive coding. This summarised a section of a participant's response into a word or phrase that are based around the topic of the response, not just an abbreviation of the content (Tesch, 2013). Next, process coding enabled the coding of actions, such as gestures participants made but were not explicitly stated by them. In-vivo coding involved taking direct quotes from participants as a code. Once these coding methods were completed, the process was repeated multiple times in 'cycles.

The final step was conceptualisation, where the qualitative codes were reviewed multiple times by the researcher and supervisors to begin to link common themes together. Figure 11 below shows a summary of this qualitative data analysis process.

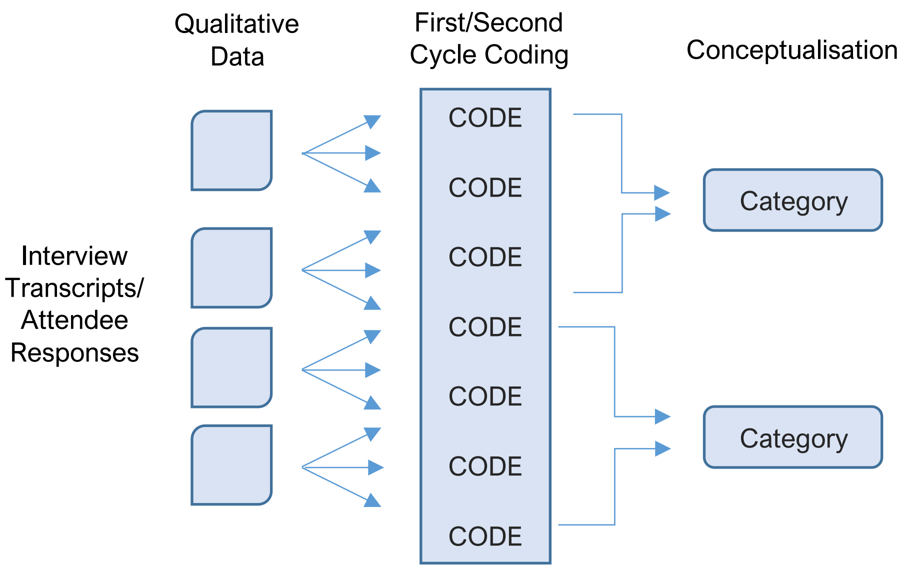


FIGURE 11 QUALITATIVE CODING PROCESS

3.3. Quantitative Methodology

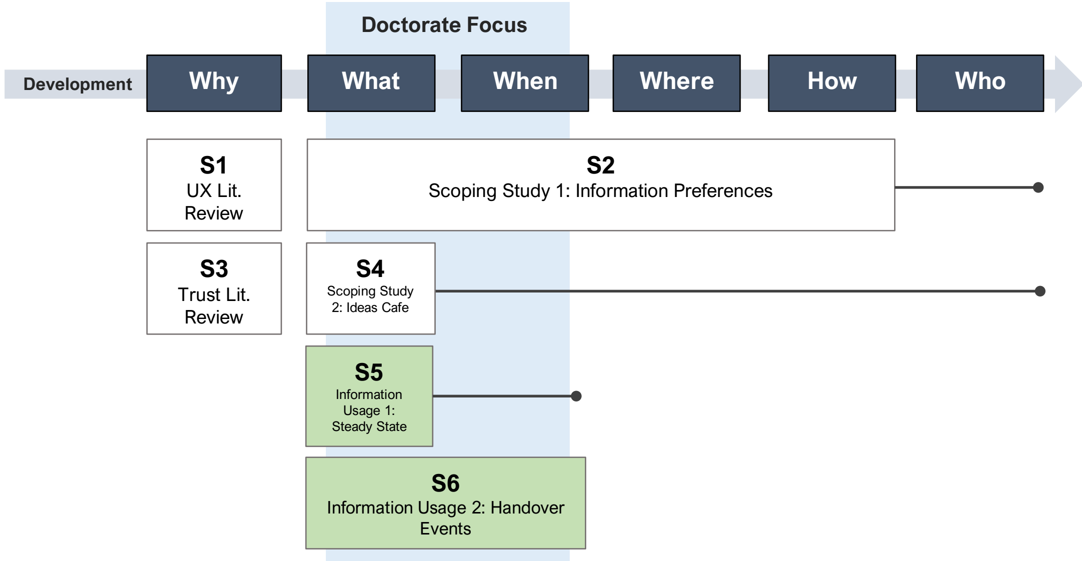


FIGURE 12 DOCTORATE OVERVIEW. SUBMISSIONS USING QUALITATIVE METHODS ARE HIGHLIGHTED

The primary quantitative method used in this doctorate was eye-tracking, used for both Information Usage Study 1: Steady State and Information Usage Study 2: Handover Events (Figure 12).

3.3.1. Eye Tracking (Submission 5 and 6- Information Studies 1 and 2)

Eye-tracking is used to understand where a participant's visual attention is focussed (Krafka et al., 2016). Owing to its popularity, there has been a focus on how more readily available technology can be used to facilitate eye-tracking, such as webcams (Papoutsaki et al., 2016) and mobile apps (Duchowski, 2017). In the automotive field, eye tracking has been typically used to assess HMI with respect to measures such as Total Eyes Off-Road Time (TEORT), Long Glance Proportion (LGP) and Mean Single Glance Duration (MSGD) (Large et al., 2016; Mehler et al., 2017; F. Vicente et al., 2015; Young, 2016). A typical measure in a HMI evaluations would assess impacts on glance behaviour to the roadway (S. A. Birrell & Fowkes, 2014; Peng & Boyle, 2015).

Measures such as TEORT were motived by guidelines published by the NHTSA such as the 2-12 rule, which recommend a maximum time period that tasks involving the HMI should be completed within (NHTSA, 2010). Outside of the automotive context, eye tracking is an established method of reviewing the usability and user experience of a broad range of products, such as in the design of websites (Djamasbi et al., 2011; Ehmke & Wilson, 2007), educational diagrams (Yusuf et al., 2007) and advertising effectiveness (Resnick & Albert, 2014).

For these reasons, eye tracking was determined to be the most appropriate choice of method to investigate the information usage inside a partially automated vehicle; providing a quantitative method of measuring what information a participant used and when they used it.

Eye-tracking records a series of gaze points, which can then be grouped into several different measures; the most common being fixations and saccades (Blascheck et al., 2017). Of interest to this doctorate are fixations; which are groupings of gaze points that are aggregated around a particular area and are of a specific length of time.

How long the duration of the aggregated gaze points should be, is an area of debate. Typically, a lower limit of 200ms has been used to determine the point at which an aggregation of gaze points become a fixation (Blascheck et al., 2017; Orquin & Holmqvist, 2018), though these appear to have been derived from a study from 1962 (Poulton, 1962). Consequently, there are suggestions that this 200ms fixation threshold is too restrictive and that cognitive understanding can be achieved in as little as 100 ms (Cutrell & Guan, 2007; Manor & Gordon, 2003; Salthouse & Ellis, 1980), particularly in the context of automotive HMI (Manor & Gordon, 2003; Orquin & Holmqvist, 2018).

The eye-tracking hardware can also impact that data. The recording frequency (measured in Hertz, Hz) determine how many gaze points are recorded every second and can range between 20-2000 Hz (Andersson et al., 2010). A higher recording frequency will reduce the number of errors in the gaze point data but ensuring a sufficient amount of eye-tracking data is collected can also ensure that these errors have a mitigated impact on the quality of the data; for example, through the use of a longitudinal experimental design.

This doctorate made use of two eye-tracking systems: the SMI system and the Tobii Pro 2 (Figure 13). Both use infrared light and cameras to track the direction of glance. The precision of eye trackers are defined as the "*the ability of the eye tracker to reliably reproduce the same gaze point measurement*" (Tobii, 2017, p. 5). A technical report into the accuracy of the SMI eye tracking system reports accuracy and precision to 1 decimal place (SMI, 2016). In contrast, a technical report into the accuracy and precision of the Tobii eye tracker reports data to 2 decimal places (Tobii, 2017). Hence, a level of 1 and 2 decimal places will be used when reporting the data collected from the SMI and Tobii eye tracking systems respectively. Both technical reports tested the eye tracking systems at a variety of distances and glance angles between the object and the participant. In all cases, the experiments in this project fell comfortably within these limits.

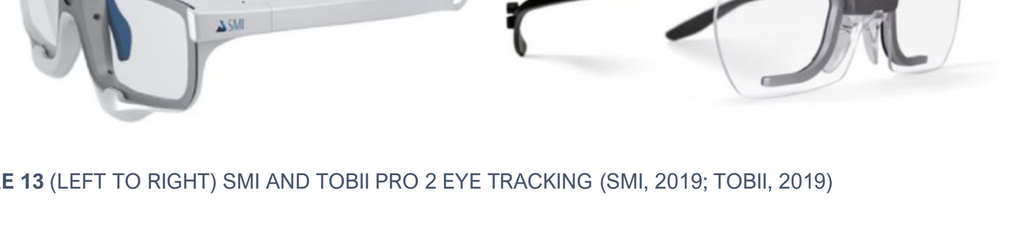


FIGURE 13 (LEFT TO RIGHT) SMI AND TOBII PRO 2 EYE TRACKING (SMI, 2019; TOBII, 2019)

All studies using eye-tracking are based on the eye-mind assumption. This assumes that the moment an object is fixated on, it is being actively cognitively processed (Kieras & Just, 2018). There are limitations with this assumption, primarily that cognitive processing can still be occurring even after a person's fixation has moved away from an object (Anderson et al., 2004; Underwood & Everatt, 1992). However, this evidence is gathered from studies that used reading tasks, and in the context of vehicles, it is justifiable to assume the connection between fixations and cognitive understanding (Crundall & Underwood, 2011); particularly considering driving is inherently a visual task (Shinar, 2008; Sivak, 1996). Consequently, the eye-mind assumption has been used a number of times to validate driving models (Yulan Liang et al., 2007; Victor et al., 2005).

3.4. Ethical Considerations

A key benefit of a driving simulator is the highly unlikely risk of a participant coming into harm. A simulated environment cannot directly cause an issue for safety; however, there were considerations around the design of scenarios. For example, there were no depictions of harm caused to any of the people in the simulation. Furthermore, health and safety regulations, for example to protect against trip hazards, were always implemented during user trials.

The most significant consideration was motion sickness. As a precaution, participants were offered water and allowed to rest between simulations. Furthermore, all studies used a familiarisation scenario to enable participants to become accustomed to the visuals and motion sickness inducing sharp turns were reduced.

All studies were reviewed and approved by the BSREC Warwick before they began (except for Submission 4- Scoping Study 2: Ideas Café, which was approved by the Coventry University Ethics Board).

- **Scoping Study 1: Information Preferences** BSREC REGO-2016-1788
- **Scoping Study 2: Ideas Café** Coventry P52764
- **Information Usage 1 & 2** BSREC REGO-2018-2196

4. Scoping Study 1: Information Preferences

Partially automated vehicles present HMI design challenges in ensuring the driver remains alert should the vehicle need to hand back control at short notice, but without exposing the driver to cognitive overload. To date, little is known about driver expectations of partial driving automation and whether this affects the information they require inside the vehicle. Twenty-five participants were presented with five partially automated driving events in a driving simulator. After each event, a semi-structured interview was conducted. The interview data was coded and analysed using thematic analysis. From the results, two groupings of driver expectations were identified: High Information Preference (HIP) and Low Information Preference (LIP); between these two groups the information preferences differed. LIP drivers did not want detailed information about the vehicle presented to them, but the definition of partial automation means that this kind of information is required for safe use. Hence, the results suggest careful thought as to how information is presented to them is required in order for LIP drivers to safely using partial driving automation. Conversely, HIP drivers wanted detailed information about the system's status and driving and were found to be more willing to work with the partial automation and its current limitations. It was evident that the drivers' expectations of the partial automation capability differed, and this affected their information preferences. Hence this study suggests that HMI designers must account for these differing expectations and preferences to create a safe, usable system that works for everyone.

Publication

Ulahannan, A. et al. (2020) 'User expectations of partial driving automation capabilities and their effect on information design preferences in the vehicle', Applied Ergonomics, 82, p. 102969. doi: https://doi.org/10.1016/j.apergo.2019.102969.

Scoping Study 1 provided the broadest set of results of all the studies in this doctorate. Considering the areas of, as highlighted below in Figure 14.

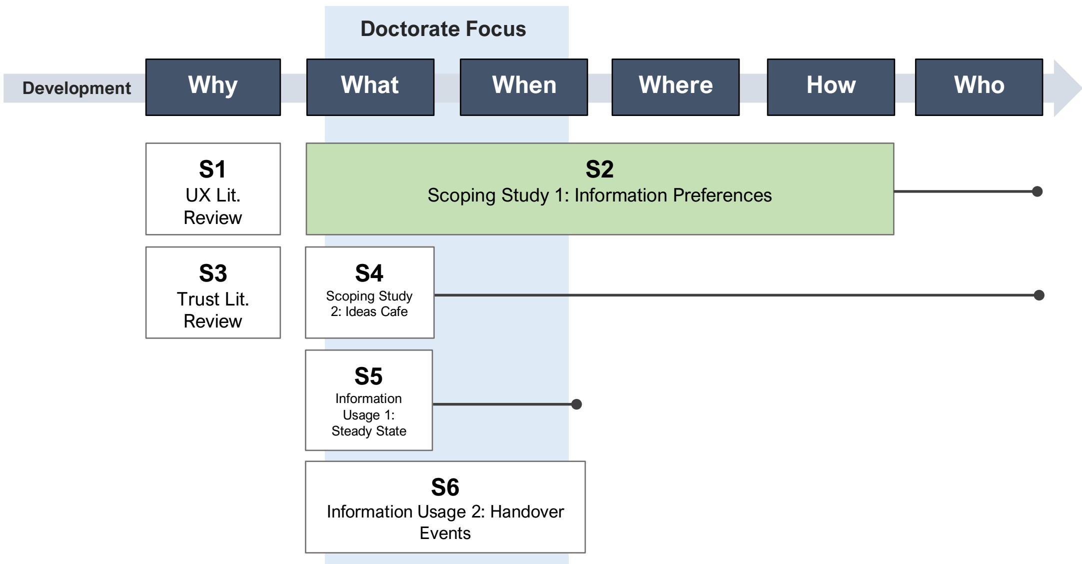


FIGURE 14 DOCTORATE OVERVIEW. SUBMISSION RELEVANT TO THIS SECTION IS HIGHLIGHTED

4.1. Aim & Objectives

4.1.1. Aim

This study aimed to understand information preferences for drivers of Level 2 partially automated vehicles

4.1.2. Objectives

- To understand what, when, where and how information should be presented to drivers of partially automated vehicles using semi-structured interviews in an immersive simulated environment
- To classify driver expectations of partially automated vehicles and understand how these affect their information preferences during the use of a partially automated vehicle.

4.2. Method

This first scoping study used the 3xD immersive driving simulator to present an eight-minute driving scenario to participants. During this scenario, playback was paused after each of the five driving events in the scenario to allow for a semi-structured interview to be conducted. The interview asked participants:

- *What* information would they like the vehicle to present?
- *Where* should this information be presented inside the vehicle?
- *When* should this information be presented?
- *How* should this information be presented?
- *How* would they expect to interact with the information?

The study is summarised below in Figure 15.

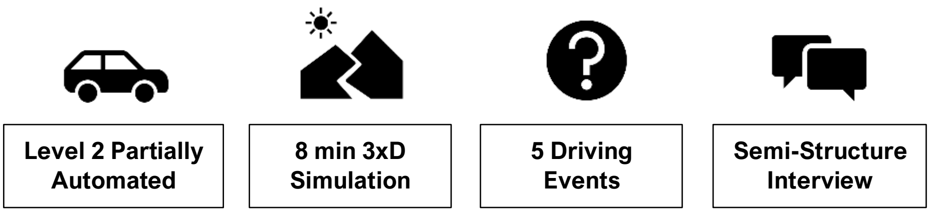


FIGURE 15 STUDY OVERVIEW FOR SCOPING STUDY 1

4.2.1. Participants

Twenty-five participants took part in the study (9 female, 16 male). All held a valid driving licence, were affiliated with the university environment and were between 18 and 39 years old (Table 3).

TABLE 3 PARTICIPANT DEMOGRAPHICS FOR SCOPING STUDY 1

Number of Participants	25
Percentage Male / Female	64% / 35%
Nationality	32% UK, 68% Non-UK
Age Ranges	18-24 (12), 25-29 (10), 30-34 (2), 35-39 (1)
Highest education level	100% Degree level
Previous Experience with Driving Simulators Yes / No	1 / 24 (participants)

Previous interview studies investigating user requirements for HMI have used a total of eight participants, citing the theoretical saturation point of the data as a reason for their sample size (Amanatidis et al., 2018; Dhillon et al., 2011). The saturation point is the point at which no additional insights emerge from the data. While eight participants may be appropriate for reaching 'code saturation' (the point at which no more qualitative codes are generated; see section 3.2.3 for a definition of 'code'); more recently, it has been found that 16-24 participants are required to reach 'meaning saturation' (the point at which no additional concepts and theories are generated) (Hennink et al., 2017). Hence, the sample size of 25 for this study was considered appropriate.

4.2.2. Driving Scenario

The 10-minute driving scenario used photorealistic LIDAR imagery (Figure 16) from the A4114, Holyhead Road in Coventry. This was a single carriageway that moved through a residential and urban environment. Within this 10-minute driving scenario, five driving events occurred; these are described below in Table 4. All vehicles and events were scripted to ensure consistency across all participants. This also included the addition of pedestrians who were not directly involved in any of the driving events during the scenario but gave a sense of realism.

TABLE 4 SUMMARY OF DRIVING EVENTS IN DRIVING SCENARIO FOR SCOPING STUDY 1

Event	Description
1 Partially Automated Driving Activation	Information required before and immediately after automated driving is turned on.
2 Following Heavy Traffic	Information required while the vehicle follows heavy, slow-moving traffic.
3 Traffic Lights	Information required when the vehicle navigates a traffic light junction
4 Steady State (non-conflict scenario)	Information required when a pedestrian runs out in front of the vehicle, which must then perform a braking manoeuvre.
5 Partially Automated Driving Deactivation	Information required before and immediately after the automated driving is turned off.

4.2.3. Interview Topic Guide

The following interview topic guide was developed based on the questions concerning the development of future HMI in partially automated vehicles (Figure 14) and used after each of the five events:

- What information would you expect to see?
- Where would the information be presented?
- When would the information be presented?
- How would the information be presented?
- How would you expect to interact with the information?

If required, a set of probes were created to assist participants in elaborating on their response and build rapport. This was done following the guidance by Leech (2002) and Turner (2010), for example, using phrases such as "*Would you elaborate on that point?*" or "*Could you give an example of that?*" (Leech, 2002; Turner, 2010). With the exception of one participant, all had never experienced a driving simulator, so it was likely a new environment for them. The interview probes were intended to help participants in case they struggled to engage in the interview.

4.2.4. Procedure

The experimental procedure was as follows:

1. Participants were invited into the WMG 3xD Simulator room, and informed consent was obtained.
2. Participants were invited to sit inside the BUC in the WMG 3xD Simulator. A summary of the vehicle's partially automated capabilities was given, including its limitations. Participants were instructed to monitor the driving task and be prepared to intervene, as they would be required in a real partially automated vehicle.
3. After each of the five events in the simulation (detailed in Table 4), the playback was paused, and the participants were interviewed using the interview schedule. The entire simulation lasted 8 minutes, and each event was approximately 1 minute long. Including the interview time between the events, participants spent a total of approximately 30-40 minutes in the simulator.
4. Participant responses were transcribed verbatim during the study by the investigator as part of the field notes.
5. To add context to the data, participants were asked to complete a demographic questionnaire. This completed the study.

FIGURE 16 3XD WITH LIDAR SCANNED IMAGERY PROJECTED

4.3. Data Analysis

There were two key sections to the data analysis, based on the two study objectives:

1. To understand information preferences in partially automated vehicles using an overall thematic analysis of all the data during each of the five driving events.
2. To understand what the driver expectations of partially automated vehicles are and how these affected their information preferences during different driving events using a holistic review of all the codes.

Part one was analysed using the coding strategy detailed in section 3.2.3, producing a detailed list of codes organised by the topic guide and the driving event (Table 5). For each code, the frequency is denoted in brackets as (f=…), indicating how many times a code was mentioned in participant responses.

Part two then abstracted the codes from the topic guide, holistically analysing how driver expectations affected the information preferences inside the vehicle. Any differences in driver expectations could be identified in the types of responses participants gave; this was then connected to their information preferences. To illustrate and give context to these differences, the data was categorised according to Geiser's Model (Geiser, 1985) and categorises information inside the vehicle into three categories: Primary, Secondary and Tertiary information. Primary information is related to the task of vehicle control. Secondary information is anything that supports the safe use of the vehicle. Finally, tertiary information are those that can enhance the driver's experience, such as GPS directions. This model gave a theoretical backing to understanding how information preferences changed between the different groups of driver expectations.

4.4. Results

Following procedure detailed in section 3.2, 719 first cycle codes were generated, detailed in Table 5 below.

TABLE 5 OVERVIEW OF ALL CODES FROM SEMI-STRUCTURED INTERVIEWS.

Event	1 Handover	2 Traffic	3 Junction	4 Steady State	5 Handover
Theme	Communication of the vehicle's situational awareness (f = 174)				
Thematic Codes	Traffic conditions and environment ahead information (75)				
	Knowing what the car will do (19)			Traffic light notification (18)	Why handover has to occur (3)
	Distance car can self-drive (8)	Distance to the next car (8)		Car in front to follow notification (3)	-
	Ensure the car is driving correctly (7)	Why the car is speeding up or slowing (5)	Confirmation car sees dangerous driving (14)	-	-
	Route and GPS (5)	Feeling of safety from real time feedback (3)	Confirmation car knows colour of light (6)	-	-
Theme	Communication of the State of Handover (f = 95)				
Thematic Codes	Self-Drive Indicator (19)				
	Countdown to handover (5)	Audio notification for unexpected belabour (6)	-	If there are traffic lights, then I won't self-drive (13)	Notification to take back control (25)
	Checklist confirmation before self-drive (2)	-	-	Forced manual mode in traffic light areas (1)	I need 'plenty' of time to get ready (6)
	Understanding who's in control (2)	-	-	-	Countdown to handover (5)
Theme	Information should be presented intelligently, or all the time (f = 128)				
Thematic Codes	Displayed all the time (37)				"In plenty of time" (16)
	When I can self-drive (9)	Only in critical situations (5)	When traffic lights can be seen (13)	Before reaching a problematic area (32)	Warnings according to driver state (9)
	-	-	-	-	Multiple notifications on approach (7)
Theme	Information should be located in existing HMIs (f = 140)				
Thematic Codes	Centre Console (43)				
	Digital Dashboard (42)				
	Heads-Up Display (33)				
	Easy, familiar access to information (22)				
Theme	Information should require minimal learning (f = 117)				
Thematic Codes	Visual Only (47)				
	Visual and Audio (39)				
	Easy to understand (6)	Spoken Audio (25)			
Theme	Limited interactions are expected when vehicle is autonomously driving (f = 65)				
Thematic Codes	-	No interaction expected (28)		-	No interaction expected- I would just take control (12)
	-	Change driving speed/style (18)		-	-
	-	Only in abnormal conditions (7)		-	-

Communication of the vehicle's situational awareness was the most frequent theme (f=174), relating closely to the theme 'knowing what the car will do', which was raised 19 times. Following this, participants requested information regarding traffic conditions and future driving conditions across all the driving events (f=74). Communication of the state of handover was the second most requested information (f=95).

Throughout all the codes, there was an overarching theme of knowing what the vehicle will do or is doing currently. Some participants requested the vehicle present a reason why it was performing certain actions, *"I'd like to know why the car is speeding up or slowing down"*.

Participants were split regarding the presentation of information, requesting either the information was displayed all the time (f=37) or more intelligently in response to road conditions (f=59). Existing HMIs was typically suggested as the location for the information (f=140), based on a consistent theme of information being easy to access across all the simulated events (f=22) and requiring minimal learning (f=117). The final aspect concerned how participants expected to interact with the vehicle while it was operating under partial driving automation. There was evidence of a split in opinion between the participants with some expecting no interaction at all (f=28) and others expecting to work with the system (f=25).

Following the initial analysis of the first cycle codes, the codes were then reviewed thematically against driver expectations of partially automated vehicle technology, to understand if there was a difference in the information preferences between the groups.

4.4.1. Driver Expectations and their Effect on Information Preferences

The researcher and their supervisor worked collaboratively to review the codes. A range of thematic groupings of codes were tested in this collaborative process. As a result of this thematic analysis process, two groupings of driver expectations were identified, based on the level of information they required in the vehicle: High Information Preference (HIP) and Low Information Preference (LIP) drivers. It is important to note, that these groupings of driver preferences are based on the result of the qualitative thematic analysis process (Maher et al., 2018; Saldaña, 2013) (previously described in more detail in section 3.2.3). Given the nature of qualitative data, it is not appropriate to calculate statistical significances between the groups. Hence, the following results should be interpreted with the understanding that a more quantitative approach would be required to state the differences between the groups with more statistical confidence. However, the value of the qualitative approach is being able to explore and discover these themes, which can then inform the design of future quantitative studies. Therefore, while the results cannot be stated with statistical certainty, it is still of value to both the EngD and the academic and industrial contributions (Ulahannan et al., 2020).

HIP participants wanted detailed information presented and had more calibrated expectations of the capability of Level 2 partial automation (calibration refers to the participant's expectation of the technology aligning with its actual capabilities). As a result, they were more willing to work with the Level 2 system. For example, a HIP participant said, "*it would be good if I could touch certain objects [on the environmental display] to make the car aware of it*".

Conversely, LIP participants expected the automation to be more capable and were less willing to work with the information provided by the system. One LIP participant said, *“I want to see where my friends are and chat with them”*. Another LIP participant said, *“It [the vehicle] should only tell me if I need to take over control”*.

Out of the 25 participants, 15 were categorised as HIP and ten as LIP. This was despite all participants being given the same description of the capabilities of Level 2 driving automation. These codes were then categorised against the Geiser Primary, Secondary, Tertiary model to illustrate the differences between the two groups for each of the driving simulation events (Table 6).

TABLE 6 INFORMATION PREFERENCES DIFFERENCES BETWEEN HIP AND LIP DRIVERS

<table>
<tr><th>Group/Events</th><th>1
Activation</th><th>2
Traffic</th><th>3
Junction</th><th>4
Steady State</th><th>5
Deactivation</th></tr>
<tr><td>HIP</td><td rowspan="2">Primary
(f=179)</td><td>Secondary
(f=190)</td><td>Secondary
(f=196)</td><td>Secondary
(f=152)</td><td rowspan="2">Primary
(f=146)</td></tr>
<tr><td>LIP</td><td>Tertiary/Primary
(f=40)</td><td>Tertiary/Primary
(f=48)</td><td>Tertiary/Primary
(f=46)</td></tr>
</table>

The thematic analysis would suggest there was no difference between the two groups of drivers for the manual driving events 1 (activation) and 5 (deactivation) (Table 6). In contrast, there were differences found for the three partially automated scenarios (Traffic, Junction and Steady State). HIP drivers consistently asked for the relevant secondary safety information to support the vehicle’s operation; in comparison, LIP drivers preferred either tertiary or primary information, but none requested secondary information. For instance, a HIP was quoted saying, “*I would want to know the car has seen the traffic light. Some kind of visual indicator to confirm it*”. In contrast, a LIP driver was not as concerned, “*The car should tell me if it’s a critical situation and I need to control it, otherwise no info needed*”. It was found that there were five times as many codes for HIP drivers compared to LIP, indicating the higher volume of information HIP drivers wanted.

Below, Table 7 shows a summary of the two HIP and LIP groups.

TABLE 7 SUMMARY OF HIP AND LIP PARTICIPANTS

High Information Preference	Low Information Preference
Wanted detailed information on the vehicle's situational awareness	Wanted less information on the status of automated driving and not concerned with assisting the partially automated system
More accepting of the limitations of partially automated driving and wanted to work with the system	Wanted the vehicle to offer assistive features
More concerned with the tactical level of driving	More concerned with the strategic level of driving

4.5. Discussion

A more detailed discussion of the information preferences results can be found in Submission 2: Interview Study. However, for this Innovation Report, these two groups of drivers were of most interest.

4.5.1. Key Results

The semi-structured interviews generated answers to the questions of *what*, *where*, *when*, and *how* information should be presented during partially automated driving. Of interest to this Innovation Report was the groupings of HIP and LIP. These groups were developed based on the participant's perceived capability of the partially automated vehicle, derived from their responses.

4.5.2. Driver Expectations and their Effect on Information Preferences

The key finding from this Scoping Study 1: Information Preferences was the classification of two driver categories of expectations, namely High and Low Information Preference (HIP and LIP) and how these two groups can affect the information preferences for partially automated vehicles.

An important finding was that for manual driving, the thematic analysis would suggest there was no difference in the information preferences for the groups. The differences were only apparent when the vehicle moved to the partially automated driving mode. This confirms the HMI design for vehicles today do not require a consideration of the driver's expectations of the vehicle capability; in comparison to partially automated vehicles when this becomes an important consideration. Many of the principles of HMI design for existing vehicles today are evident in the partially automated systems being introduced (P. Olsen, 2018); this study has shown this to be problematic. For example, the aforementioned Tesla Autopilot system does not show recognition of the differing expectations of drivers and hence their varying information preferences.

By definition, Level 2 partial automation requires the driver to pay attention at all times during automated driving, regardless of the two groups of driver expectations. The subset of users who struggle to monitor automated processes have been evident in previous studies looking at the difficulties of such a task (Dzindolet et al., 2003; Kaber & Endsley, 2004; Sheridan, 1995) and this has been shown to cause riskier driver behaviour (Banks, Eriksson, et al., 2018). For future HMI design, the results suggested that LIP drivers will require careful thought as to the information that is presented to them to keep them engaged and to avoid frustration with the HMI. Conversely, HIP drivers exhibit the characteristics to be the most appropriate user of partial automation, with their acceptance of technological limitations and willingness to work with the secondary information provided by the system.

By understanding that these differing preferences exist, HMI designers can be better equipped to ensure that information can be communicated effectively, regardless of the driver's predisposition. For example, adaptive HMIs, those that can adjust HMI elements depending on the driving event, may be the solution to catering to differing driver preferences and expectations (Alhazmi et al., 2015; S. Birrell et al., 2017; Tchankue et al., 2011).

4.5.3. Limitations

The main limitation of the study was that the demographics of participants were exclusively those who were related to the University environment. The demographic was mainly a result of the study being primarily advertised in the university community. While this means the sample will not be representative of the large population of the UK, this is not as problematic for the results. The age demographic of the recruited participants means the results are focussed on understanding future customers of automated driving technology. Younger age demographics have been shown to utilise newer technologies faster than older demographics, with technology literacy being observed in younger ages (Burnett, 2010; Hargittai & Hinnant, 2008; Teo, 2001). Along with the support of Jaguar Land Rover, this age bracket was deemed appropriate for the motivations of the study to understand information requirements for users of partially automated vehicles.

4.5.4. Methodological Recommendations

It was noted that many of the responses from participants were based around information and HMIs that exist today in vehicles. This effect has been observed previously in the field of prototype testing, where high fidelity products appeared too ‘complete’ and hence users were less able to suggest ways to improve upon them (Hall, 2001; Rudd et al., 1996). It may be the case that a lower fidelity vehicle inside the simulator may have given participants the ‘freedom’ to suggest more changes and ideas.

4.6. Conclusion

This study set out to understand the area this doctorate was going to focus on. To achieve this, it used a semi-structured interview format to perform a broad inquiry into the key challenges facing the area of HMI inside partially automated vehicles (*what*, *when*, *where*, *how* and *who*).

Scoping Study 1: Information Preferences has shown that drivers of partially automated vehicles can have varied information preferences which can impact how safely they can use the partially automated vehicle. These varied information preferences were labelled as High Information Preferences (HIP) and Low Information Preferences (LIP) drivers. These groupings also affected the information drivers required during various driving events. For example, primary or tertiary information was preferred by LIP drivers, whereas HIP drivers preferred more secondary information to work with the system and ensure its correct use. There was an overarching theme of participants wanting to know what the vehicle was doing and what it will do to varying degrees of detail. In some cases, participants also want to know why it was performing the actions it was.

If future HMI fail to recognise that information preferences can vary and this can affect how a driver will use a partially automated system, then HMIs may not provide the appropriate support. Studies have found this to be evident in Level 2, partially automated driving available today.

These driver groupings provided the important first step in the challenge of designing HMIs for future automated vehicles. Scoping Study 1: Information Preferences highlight the significant challenges with understanding *what* information needs to be shown to participants and *when* it should be presented, before considering *where* and *how* it should be presented. However, the participant demographics, while a valid and important subset, do limit the generalisability of this first study; hence there was a requirement to address this.

After completion of this study, there was an opportunity for the doctorate to be involved in the design of a large scale public engagement event. The event was an opportune chance to explore the questions of what information drivers require inside partially automated vehicles; leading to the design of Scoping Study 2: Ideas Café.

5. Scoping Study 2: Ideas Café

Scoping Study 2 used the Ideas Café format to investigate the factors that affect driver trust in partially and fully automated vehicles. 35 attendees came to the event held at the Coventry Transport Museum. Four emergent themes were noted as drivers of trust in automated vehicles: Society & Policy, Data & Privacy, Internal HMI and Inclusive Design. All of themes had an overarching theme of the importance of communication. Of interest to this study was the internal HMI theme, which validated many of the results from the first scoping study: understanding what information needs to be presented inside the vehicle is critical to achieving the appropriate trust and usability.

Publications

Ulahannan, A., Cain, R., Dhadyalla, G., Jennings, P., Birrell, S., Waters, M. and Mouzakitis, A., 2018 Using the Ideas Café to Explore Trust in Autonomous Vehicles. In International Conference on Applied Human Factors and Ergonomics (pp. 3-14). Springer, Cham.

Ulahannan, A., Cain, R., Dhadyalla, G., Jennings, P., Birrell, S., Waters, M. 2018 The Ideas Café: engaging the public in design research. In Proceedings of DRS 2018: Catalyst Vol. 1 (p.1175-1193).

Chronologically, at this point in the EngD (Figure 17), the development of driver trust and the role that the internal HMIs can play was of specific interest. What information should be presented to drivers and when was found to be a key result in the previous Scoping Study 1 from a usability perspective, but its link to the development of trust was unclear as trust was never measured. Hence the Ideas Café aimed to address this by attempting to understand what factors affect the development of trust in partially to fully automated vehicles. The level of vehicle autonomy was also broadened to ensure the doctorate could appropriately explore all research opportunities. This helped avoid narrowing the doctorate too early onto information requirements and to explore other trust development factors.

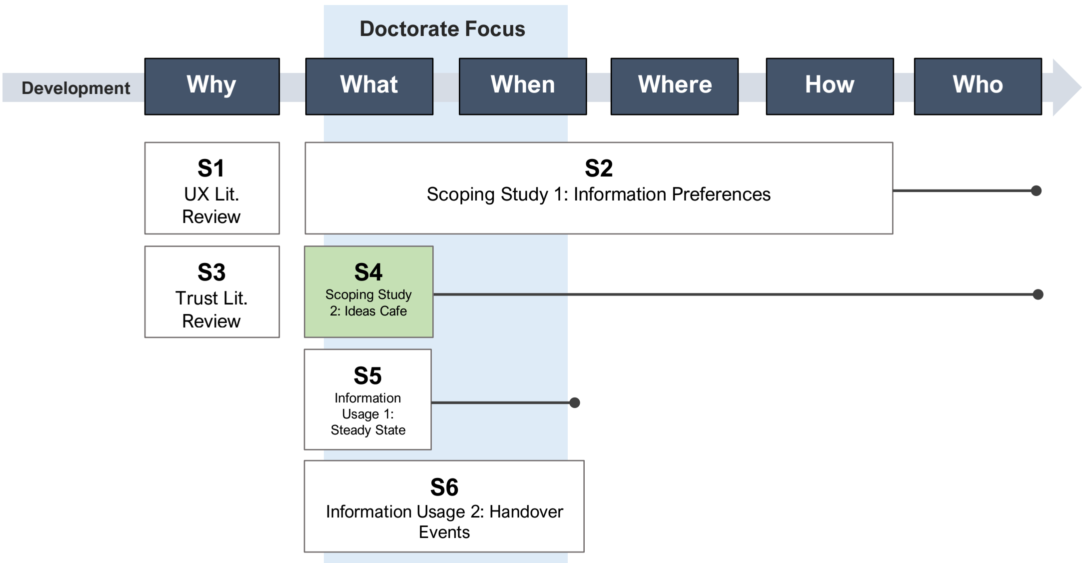


FIGURE 17 DOCTORATE OVERVIEW. SUBMISSION RELEVANT TO THIS SECTION ARE HIGHLIGHTED

5.1. Aim & Objectives

5.1.1. Aim

To understand what factors affect a driver's trust in partially or fully automated vehicles.

5.1.2. Objectives

- To design and run a public engagement event to explore factors affecting trust in partial and full automated technology
- To understand information preferences for the internal HMI of a partially automated vehicle

5.2. Method

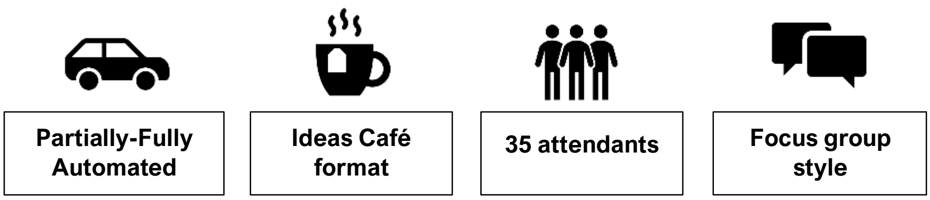


FIGURE 18 STUDY OVERVIEW FOR SCOPING STUDY 2

Figure 18 above details the study design for Scoping Study 2: Ideas Café.

One of the most important factors in the success of an Ideas Café is the location, which was chosen as the Coventry Transport Museum (Baker et al., 2005). The central location provided convenient access for potential attendees in the local areas around Coventry. Furthermore, free public transport was arranged. The transport museum also felt most appropriate to discuss issues around future vehicle technology given Coventry's rich motoring heritage and that environmental cues can help attendants engage with the event (Berger & Fitzsimons, 2008). Figure 19 below shows the exterior of the museum along with a photo of the interior during the event.

FIGURE 19 COVENTRY TRANSPORT MUSEUM, JUNE 2017. (PHOTOS OF PARTICIPANTS ARE USED WITH CONSENT)

Given the large number of participants targeted, the recruitment strategy was important. Through the use of promotional web pages, social media marketing and physical promotion, the event was able to register 35 attendants for the day.

Note that the term 'driverless car' was used for the event as it was deemed most appropriate at the time for attendees who may not have been familiar with the terminology such as 'partially/fully automated vehicle'.

5.2.1. Attendants

35 attendees arrived on the day from a range of different age demographics and occupations. These are summarised below in Table 8.

TABLE 8 ATTENDEE DEMOGRAPHICS FOR SCOPING STUDY 2

Demographic	Number
Age	18-24 (2), 25-34 (5), 35-44 (9), 45-54 (9), 55-64 (5), 65-74 (1), 75+ (4)
Gender	Male (23), Female (11), Prefer not to say (2)
Occupation	Retired (9), Academia (6), Student (5), Engineering (5), Government (4), Unknown (4), Charity (1), Publishing (1), Marketing (1)

Attendees were seated over six tables, resulting in approximately six to eight attendees per table. The Ideas Café format draws many parallels with workshop events, where six to eight participants per table were the recommended group sizes per table (Carson, 2011). The total attendance of 35 was considered appropriate given the justification for the previous Scoping Study 1, where 16-24 participants were required to reach 'meaning saturation' (Hennink et al., 2017).

5.2.2. Agenda

Organising a large number of attendees required a clear agenda for the day and used a mixed methods approach to maintain the interest of attendants in the event. These summarised below in Figure 20. Throughout the entire event, attendees were free to collect refreshments such as coffee, tea and cake at any time.

FIGURE 20 AGENDA FOR THE IDEAS CAFÉ. RELEVANT DATA COLLECTION IS HIGHLIGHTED IN GREEN

As highlighted above in Figure 20, the data collected and analysed for this doctorate was a subset of the data collected during the event day. The items of interest to this study are highlighted in green in Figure 20 and are summarised in detail below:

- **Spectrum Lines**: Attendees were asked to stick a paper person on a semantic scale in response to the question "*Do you think driverless cars are a good idea?*" This was completed twice, once at the start of the event and again as participants were leaving. This activity aimed to get a real-time visual indicator of attendee perceptions in the room.

By repeating the exercise at the end of the event, the goal was to quantitatively understand if the Ideas Café affected attendees' perceptions of automated vehicles.

- **Table Session 1 Trust**: The majority of data collection occurred during the table sessions. Each table was accompanied by a table facilitator who ensured all attendants had the opportunity to contribute. An important factor was ensuring consistency in the data collection between the tables of attendees. For this reason, the researcher moved between the different tables to ensure that data collection was consistent between the groups. Furthermore, all table facilitators received a detailed topic guide and were instructed to follow the questions as carefully as possible. Stimuli were provided for each table to assist with discussions but aside from the initial question of "*What would help you trust a driverless car?*", tables were left mainly to their direction. Attendants were encouraged to write all their thoughts on post-it notes, and facilitators took field notes. (Note: session two was organised by another collaborating academic and not relevant to this study)

Below Figure 21, shows the spectrum line activity.

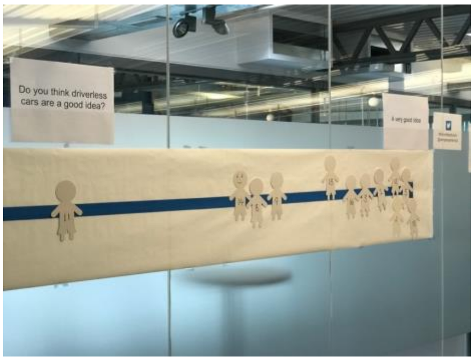


FIGURE 21 SPECTRUM LINE WITH SOME RESPONSES

Figure 22 shows some of the stimuli provided to participants to help the table conversations. Stimuli such as the mock newspapers were based on popular news stories at the time of the event.

FIGURE 22 (LEFT) NEWSPAPER STIMULI, (RIGHT) PARTICIPANT PACK WITH MATERIALS FOR THE SPECTRUM LINE

5.3. Data Analysis

The data collected from the event is broad and required additional analytical strategies in comparison to the previous qualitative Scoping Study 1.

- **Spectrum Line Analysis:** The semantic scale employed did not feature any markings, so the locations of the participants' responses needed to be measured. Panoramic photography was used to capture a photo of the semantic scale (necessary as the line was 5m long and would not fit within the field of view of the camera). Measurements were then taken digitally on the photograph for the locations of each response. The Wilcoxon Test was used to determine differences between the two datasets.
- **Session 1 Trust:** All attendee notes and facilitator field notes were transcribed verbatim into NVivo. From there, the same qualitative analysis procedure as described in 3.2.3 was used.

5.4. Results & Discussion

Given the broad and exploratory nature of the event, it was deemed more appropriate to present the results and discussion together. This section will analyse each of the methodologies and implications of each result on this doctorate and the broader field of information requirements inside automated vehicles.

5.4.1. Spectrum Lines

The aim of the spectrum lines was to get a real-time visual indicator of attendee perceptions in the room. A Wilcoxon test revealed that there was no significant difference between the scales before and after the event (p= 0.561).

The result suggests that the event did not have a significant effect on attendee perceptions of automated vehicles. While one of the key aspects of Ideas Cafés is the two-way flow of information, this event's aim focussed on giving attendees a platform to share their ideas and thoughts and not to influence their perceptions of the technology. Figure 23 below illustrates the pre and post-event results diagrammatically.

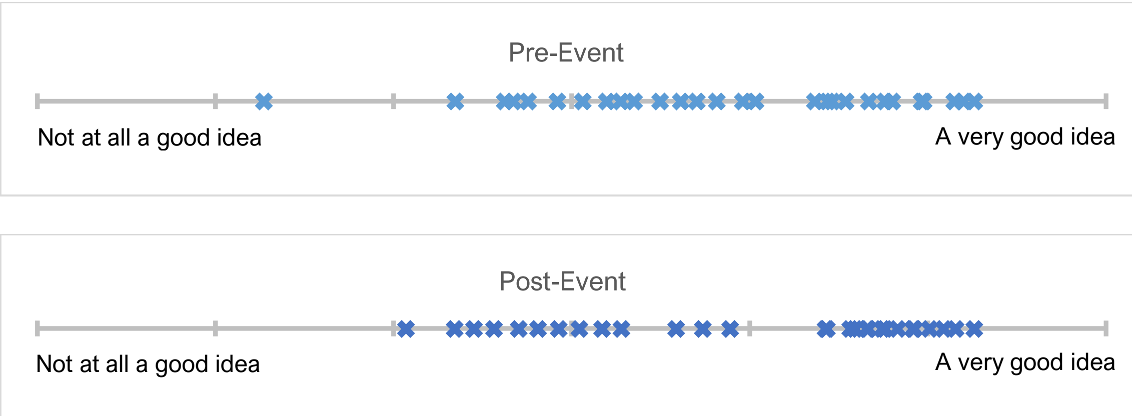


FIGURE 23 PRE AND POST EVENT SPECTRUM LINE RESPONSES

5.4.2. Table Sessions

General Overview of All Themes

The table sessions covered a broad range of topics and generated themes relating to society and policy, data and privacy, inclusive design principles and, of interest to this doctorate, the vehicle's internal HMI. All the key emergent themes and their comprising thematic codes can be seen below in Figure 24.

Society and Policy (f=49)

- Vehicle Brand
- Coexistence of traditional and self driving vehicles
- Service and Maintenance
- Legal, Regulatory
- Infrastructure
- Adoption of Technology
- Physical Privacy
- Concerns with no driver

Data and Privacy (f=45)

- Safety Risk
- Acceptance data is shared
- Differntial Privacy
- Unaware of sharing
- Targeted Advertising
- Data Storage
- Reasons why

Internal HMI (f=37)

- Capabilties of Vehicle
- Reliability
- Aesthetics
- Driving Style Adjustments
- Customisable Privacy

Inclusive Design (f=29)

- Accesibility Issues
- Involve People in Design
- Age Issues
- Pedestrians

FIGURE 24 ALL EMERGENT THEMES FROM THE IDEAS CAFÉ TABLE DISCUSSIONS

Society and policy was the biggest driver of trust for attendees. Attendees were concerned about how the new technology could be integrated with vehicles today, both on the road and in terms of servicing and repair. There were also concerns around data and privacy and the implementation of safeguards. Some participants were more sceptical about the usage of their data, "*Self-driving cars are open to cybersecurity threats, more susceptible to terrorism"* whereas others were more resigned to the fact that their data may be shared, "*I accept that most of my data is already out there, especially my location*". Another emergent theme was concerned with inclusive design, with participants indicating the importance of involving many different stakeholders in the design process, "*Technology can be trustworthy, but it needs to start from a certain group of people (and not engineers) to ensure that it's working*" and "*Involve the public, bus and taxi drivers should be involved*".

One theme was evident across all the emergent themes was communication. As one attendee commented, "*Requires unbiased communication towards building trust*". For codes related to society and policy, attendees wanted clear communication from those responsible for implementing the new technology (such as policymakers and automotive companies). For the theme of data and privacy, attendees wanted to know why data was being collected and the associated risks. The theme of inclusive design is, by definition, centred around ensuring the accessibility of the product or service for all users. Finally, for the internal HMI, attendees wanted clear communication of its capabilities.

It is the overarching theme from this event that communication is the key to building trust across all the challenges in the area. Good communication has previously been observed as critical to the success of a change initiative (Bordia et al., 2004; Kitchen & Daly, 2002). In the previous Scoping Study 1, participants wanted to know what the vehicle was doing; in other words, the communication was critical. It was interesting to observe that the despite the broader demographic and the open-ended question of "*what would help you trust a driverless car*", the topic of what information the vehicle presents was prevalent in responses, similar to the Scoping Study 1.

Summarised below in Figure 25 are the codes specifically related to the internal HMI. Similar to the Scoping Study 1, frequencies were counted for each of the themes and are denoted in brackets as (f=…) in the following discussion.

Internal HMI

Concern around these future vehicle's capabilities and reliability was one of the most common themes (f=19), and attendees appeared to draw on their personal experiences of technological failings from other products, "*Technology can go wrong, it can do a lot of damage*" and "*Computer systems are not all they should be*". Some attendees made specific references to different driving conditions, "*can it be trusted with speed limits?*" and "*can it be trusted with last-minute changes?*". It has found this is also the case in vehicle's today, with the capability and safety of the vehicle being the highest-rated factors in purchasing decisions (Koppel et al., 2008; Vrkljan & Anaby, 2011).

However, the question remains as to how capabilities should be communicated? Koppel et al. (2008) found that in order to assess the safety and capability of a vehicle, parameters such as EuroNCAP are used, but a similar figure is unavailable for partially automated vehicles. To attain comparable statistics would require hundreds of millions of miles of testing to prove safety (Kalra & Paddock, 2016), making it impractical to ascertain today.

It would appear that there are only two methods that can support drivers in communicating the vehicle's capabilities. First, is to provide sufficient pre-education before using the system. This concept of informed safety was first proposed by Khastgir et al. (2018a), so that drivers are aware of the system's ODD (Khastgir et al., 2018a). When drivers are provided with information prior to system use, the system could be appropriately used (Beller et al., 2013). Second, (and the main focus of this doctorate), drivers could be provided with capability and safety information during the use of the system through the vehicle's HMI. Hence to achieve this communication of the vehicle's capabilities, there must be an understanding of what information should be presented to achieve this.

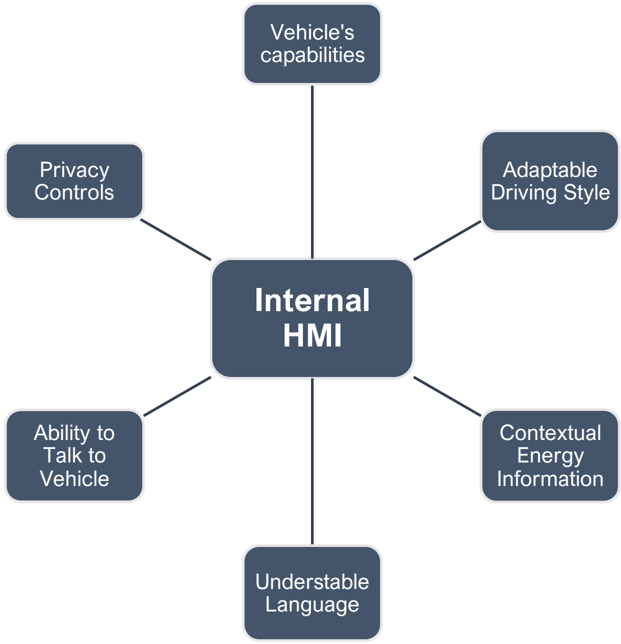


FIGURE 25 SUMMARY OF THEMES RELATED TO INTERNAL HMI

The other theme closely related to the vehicle's communication of its capabilities was ensuring the vehicle communicated clearly in a manner that was easy to understand. For example, one attendee stated, "*Should be controllable by all, not just technologists*". Another attendee said, "*Would the technology be too complicated for the average person?*". There was a consensus that the HMI or information presented needed to be easy to understand. This was highlighted again by the need for contextual information about energy use. For example, rather than presenting a reading of watt-hour usage, information could be presented as the equivalent number of light bulbs. Again, this was another recurrent theme from the first scoping study and is strongly associated with the need for the driver to have a robust mental model of the vehicle's actions (Hellström & Bensch, 2018; Kieras & Bovair, 1984).

An adaptable driving style was also a reoccurring theme from the first scoping study, "*I would like a driving style tailored to culture and location*". The remaining themes of privacy controls and the ability to talk to the vehicle are out of the scope of this doctorate but highlight important areas that a future HMI must consider.

5.4.3. Comments on Methodology

The Ideas Café aimed to address the demographic limitations of Scoping Study 1 and to reaffirm the themes found. A feedback questionnaire was given to attendees after the event and the response was positive. 52% of participants were extremely satisfied with the event, 32% were satisfied. The feedback would suggest that the event was successful in engaging a large group of attendees in conversation around the topic of automated vehicles. Two attendees complained of the event being too noisy and the pace being too fast. It was reassuring that this was only voiced by two attendees out of the 35.

The financial cost, time, recruitment and resource intensive requirements are another limitation of the Ideas Café methodology. In hindsight, putting the event on the weekend may have been more effective as opposed to a Friday afternoon. It also required several experienced facilitators and a host who can manage the activities around the room.

With this being said, there are few methods that are able to bring 35 people simultaneously to develop the kind of rich data the event produced.

5.5. Conclusion

The Ideas Café event was a unique opportunity to collect a broad range of opinions from many attendees in a relatively short space of time. Creative methods were employed (spectrum lines and table sessions). Attendee feedback was positive, suggesting it was successful in involving this large group of people.

The event provided the opportunity to explore the development of trust in automated vehicles. This was to ensure all possibilities for the doctorate's overall direction were explored. The Ideas Café provided a number of important confirmations of results from Scoping Study 1. Though there were a broad set of emergent themes from the event (society and policy, data and privacy, internal HMI and inclusive design), there was a cross-cutting theme of the importance of communication; whether it be between policymakers and the public, or between the driver and the vehicle. Focussing on the results most relevant to this doctorate, the importance of communicating the capability and safety of the vehicle was emphasised by attendees. Scoping Study 1 confirmed this from a user preference/usability perspective; Scoping Study 2 confirmed this from a trust perspective, what information is presented to drivers is crucial for both the usability of the vehicle and the development of trust. Other themes were also recurrent, such as adaptable driving styles and the need for an understandable HMI language.

Based on the results from the two Scoping Studies, there was evidence to move forward with focussing the doctorate on quantitatively defining what information drivers use inside a partially automated vehicle and when this information should be presented. Hence the focus for future studies in this doctorate was around understanding the information usage inside a partially automated vehicle so that HMIs for can be more appropriately designed to support the driver in the use of the system.

6. Adaptive HMIs as a Solution

Scoping Studies 1 and 2 have highlighted the importance of understanding what information drivers of future partially automated vehicles require inside the vehicle. In the research leading to the design of the Information Usage studies (that follow the end of this Section), it became evident that adaptive HMIs could provide a solution to the HMI challenge for these future vehicles and the literature is discussed. One of the big questions remains around how the information should be adapted. Given the effect that time has on trust, workload and experience, it became evident that this may be an appropriate method of adapting an HMI. This led into the longitudinal design of Information Usage Study 1.

In the introduction of this Innovation Report, it was discussed that despite the research strongly suggesting the contrary, the approach in current HMI design in partially automated vehicles has been to provide the driver with as much information as possible in the hope that some of the information will be processed and keep the driver situationally aware (P. Olsen, 2018). The associated negative consequences with this approach, such as cognitive overload and disengagement with the monitoring task, have been observed in real-world partially automated driving today (Lyu et al., 2017; Manawadu et al., 2018; Merat et al., 2014). Scoping Studies 1 and 2 have demonstrated that to begin to design an HMI that can support drivers in using these systems, the first question of *what* information should be presented needs to be answered.

One of the solutions that have been proposed is the idea of an adaptive HMI, to ensure that drivers remain engaged with the monitoring task in a partially automated vehicle (Riener et al., 2016). An adaptive HMI can modify the information presented to the driver according to a particular driver of adaption (Sarter, 2007). This change in information presented can be achieved by adding it, removing it or by reducing its visual prominence on the vehicle's information display; enabling other information, that would be considered more appropriate for that particular instance, to increase in visual prominence in its place.

Consequently, there are two aspects raised for future research. The first is how visual prominence can be manipulated to achieve the aforementioned effect in HMI design. The second around what the driver of information change should be.

Addressing the first, visual prominence is a measure of how easily a user can access the information on an HMI. The field is well established with studies covering a wide range of aspects in understanding how visual prominence can be achieved, particularly in the design of HMIs (Yongqiang Liang et al., 2018; Lindberg & Näsänen, 2003; Rigou et al., 2018). However, for this doctorate, understanding how visual prominence should change was out of the scope. Considering the doctorate overview diagram (Figure 7), the topic of visual prominence is concerned with the question of *how* information requirements should change. This doctorate was focussed on *what* the information requirements are.

Considering now the driver of information adaption, there are two approaches: the aforementioned automatic adaptive HMI and an adaptable HMI (Stuerzlinger et al., 2008). Though the words are similar, there are important differences in what they entail. On an adaptable HMI the user can control the information displayed and hence is a more straightforward solution; the user is always in control of what information they are presented with and there is a lower risk of confusion (Sarter, 2007). However, there is evidence to suggest that users are not the best judge of the information they will require in a partially automated vehicle (Andre & Wickens, 1995; Bailey, 1993). The results from Scoping Study 1 would also suggest the same thing, with the two groupings of HIP and LIP drivers being evident. The issue is that no research to date has defined what the information requirements should be, so it is unknown whether users are best placed to choose the information they need for themselves.

Conversely, an adaptive HMI is automatic in its selection of information. But the driver of this change is less clear (Scerbo, 2018). Some have suggested using driver performance and modelling (Morrison et al., 1993). Performance can be managed by comparing current performance against expected/average values to adapt information presentation accordingly. This then raises questions as to what these measures of driving performance are and is less applicable in the context of partially automated vehicles, where there would need to be a measure of monitoring performance, not driving performance. Workload has also been suggested as a potential driver for information adaption (Brostrom et al., 2006; Piechulla et al., 2003). Some concepts have attempted to identify abnormal stress and workload in the user and adapt the HMI accordingly (Hancock & Chignell, 1988). This relates closely to work that has investigated physiological measures to drive the adaption of information (Hollnagel & Woods, 2005; Morrison et al., 1993). Developing accurate physiological measures inside the vehicle is one of the challenges for this approach.

One of the final drivers of adaption explored to date is the temporal effect of a driver's developing experience with a partially automated system (Hussain et al., 2018; Sarter, 2007). This temporal effect is well understood, such as in the development of trust (Khastgir et al., 2018a) and how the driver uses the vehicle. For example, with time and experience, drivers of electric vehicles are able to develop adapted strategies for managing range issues and energy usage while driving (Neumann et al., 2015). In other domains, it is recognised that how a user rates the usability or experience of a service is dependent on the length of their experience (Kujala et al., 2017).

Yet to date, there were no studies that have looked at how the driver's developing experience affects their information requirements. Of all the measures described, it appeared that temporal effects had not been considered with regards to information adaption.

At this stage in the doctorate, having developed a strong justification for researching *what* information requirements are inside partially automated vehicles, the next step is to attempt to quantify these requirements. With adaptive solutions being proposed as a solution, the doctorate now attempted to understand how such an adaption of information could be achieved. It required a study that could investigate what information drivers needed and understand how this changes with increasing exposure to the automated system; hence to understand if the temporal factor of experience can be used as the driver of information adaption. This was the lead into Information Usage Study 1.

7. Information Usage Study 1: Steady State

With Scoping Studies 1 & 2 providing the foundation to explore what the information requirements for drivers of partially automated vehicles are, the next study aimed to define these requirements quantitatively and they changed over time. Adaptive HMIs, those that automatically change the information presented based on a number of factors (workload, temporal, physiological), have been previously proposed as a solution, but little is known about how information should adapt in a partially automated vehicle during continuous steady state driving. This study aimed to classify information usage based on driver experience to inform the design of a future adaptive HMI in partially automated vehicle. The unique feature of this study over existing literature is that each participant attended for five consecutive days, enabling a first look at how information usage changes with increasing familiarity. This also provided an important first methodological contribution to future HMI user trial study design. Seventeen participants experienced a steady state automated driving simulation for 26 minutes per day a driving simulator, replicating a regularly driven route, such as a commute into work. Nine types of information, representative of future partially automated vehicle HMIs, were displayed on a tablet and eye tracking was used to record the information that the participants fixated on. The results found that information usage did change with increased familiarity, with significant differences in what information participants looked at between the first and last trial days. Participants tended to view information confirming the technical competence over system transparency information about the future state of the vehicle. On this basis, HMI design recommendations are made, in particular in regard to the design of more intelligent and adaptive HMIs for future partially automated vehicles.

Publications

Ulahannan, A. et al. (2020) 'Designing an Adaptive Interface: Using Eye Tracking to Classify How Information Usage Changes Over Time in Partially Automated Vehicles', IEEE Access, 8, pp. 16865–16875. doi: 10.1109/ACCESS.2020.2966928.

Ulahannan, A., Birrell, S., Thomson, S., Skyrpchuk, L., Mouzakitis, A., 2019. The interface challenge for semi-automated vehicles: how driver behaviour and trust influence information requirements over time. Intelligent Vehicles Symposium 96–101.

Scoping Studies 1 & 2 confirmed the importance of understanding what information drivers require inside partially automated vehicles; the next step in the doctorate was to begin to define these requirements quantitatively and understand how they may change with increasing familiarity to the system. There was no previous research that investigated these longitudinal effects. Figure 26 below shows how Information Usage Study 1: Steady State (IUS1) addresses the questions of *what* and *when*.

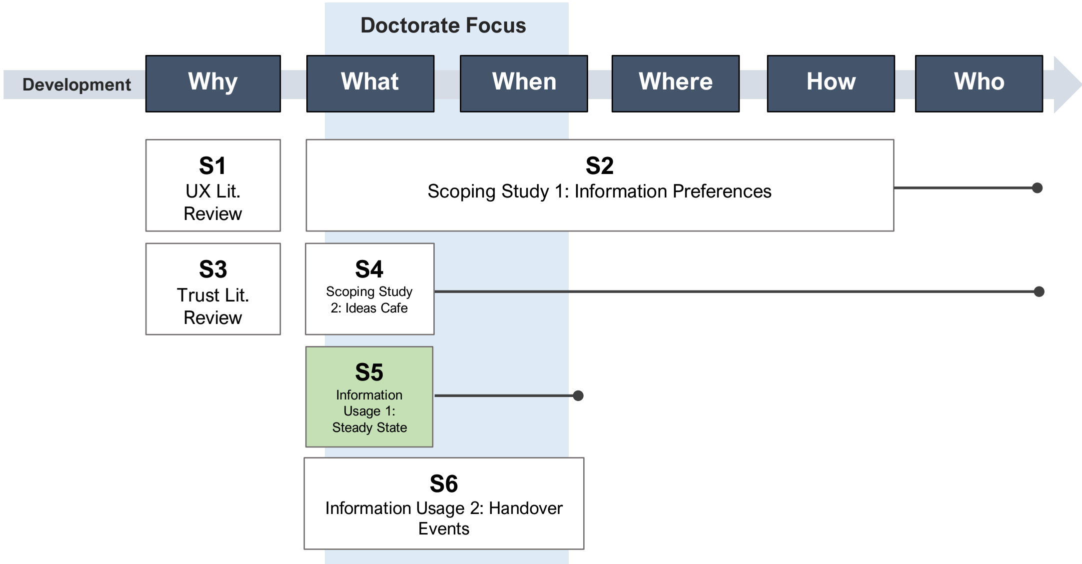


FIGURE 26 DOCTORATE OVERVIEW. SUBMISSION RELEVANT TO THIS SECTION IS HIGHLIGHTED

In Information Usage Study 1: Steady State (IUS1), other aspects drivers that may have affected information usage were explored. The Driver Behaviour Questionnaire, a 24 point questionnaire exploring the driver's past driving experiences, was given to participants (Parker et al., 2007). Next, to measure trust, the Jian Scale was used (Jian et al., 2000), a self-report scale of seven questions. Finally, a subjective information preferences questionnaire was given. However, for the purposes of this Innovation Report and the aim of investigating the information requirements in partially automated vehicles, these have been omitted from this Section, but can be found in Submission 5.

7.1. Aim & Objectives

7.1.1. Aim

To classify the information usage of drivers of Level 2 partially automated vehicles during steady-state driving to begin to inform the design of an adaptive HMI

7.1.2. Objectives

- To develop a shortlist of information types for partially automated vehicles based on the two previous scoping studies, regulatory standards and collaborations with Jaguar Land Rover.
- To measure the overall percentage of time participants spent fixating on an information display
- To measure the overall fixations to each information type
- To measure how fixations to each information type changed over the week as participants became increasingly familiar with the partially automated system

7.2. Method

FIGURE 27 STUDY OVERVIEW FOR IUS1

A summary of the study overview can be found above in Figure 27. Methodologically, the study presents two challenges. First was to design an experiment that would expose a participant to a partially automated driving scenario, while being presented with various information about the vehicle and using eye-tracking to measure the fixations to the information. The second was to repeat this over a period of time to understand how increasing exposure to the system affect information usage.

7.2.1. Study Design

The study exposed participants to a 13 minute, partially automated driving simulation inside the WMG Dev Sim, twice per day. During each simulation, participants were presented with nine information types (the selection of which will be discussed later in section 7.2.3) presented on an iPad Pro surrogate dashboard display. Eye-tracking glasses were used to record what information participants fixated on, and when. The number of fixations to each information type was recorded. To understand how the information usage changed with increasing exposure, the study used a longitudinal 5-day within-subjects design.

As discussed in the previous Section, no studies had explored information requirements for partially automated vehicles over a period of time. Hence, there was no possibility of benchmarking the methods against others. For this reason, a length of time had to be chosen based on practical and scheduling considerations. Five consecutive days was considered the maximum length of time that a participant would be willing to partake and also long enough to be able to observe a change in information usage. Methodologically, Information Usage Study 1: Steady State importantly contributed to a better understanding of how longitudinal studies in driving simulators could be conducted.

A summary of the study design can be seen below in Figure 28.

Mon	**Tues**	**Wed**	**Thur**	**Fri**
Briefing	**Sim 1**	**Sim 1**	**Sim 1**	**Sim 1**
Sim 1	**Sim 2**	**Sim 2**	**Sim 2**	**Sim 2**

FIGURE 28 STUDY DESIGN FOR IUS1

7.2.2. Participants

Initially, 20 participants were recruited for this study through advertising around the University of Warwick campus; using email advertising and flyers around popular communal areas around campus. The inclusion criteria asked for any participant who was over the age of 18 years old and held a valid driving license (UK/EU and International).

As a recompense for their time, participants were given £5 for each day of simulations they attended. If they completed all five days then they would receive a bonus of £5, hence a participant who attended all five sessions was paid £30.

A total of three participants withdrew from the study in the middle of the trial week as a result of scheduling issues. These participants were removed from the dataset as their incomplete data caused issues for the statistical data analysis. A detailed breakdown of the participants who completed all five sessions can be seen below in Table 9.

TABLE 9 PARTICIPANT DEMOGRAPHICS FOR IUS1

Demographic	Number
Gender	8 (Male), 9 (Female)
Age	2 (18-24), 11 (25-34), 1 (66-64), 3 (65 or older)
Driving Experience	1 (< 1 year), 3 (3-5 years), 13 (More than 5 years)
Miles per Year	3 (0-4000), 7 (4000-8000), 7 (8000-12,000)
Driving Days per Week	2 (Once), 3 (2-3), 1 (4-5), 2 (5-6), 8 (Daily)

For this first longitudinal investigation into information usage, the study targeted twenty participants. Previous studies that have used driving simulators in combination with eye tracking have used a variety of different sample sizes, such as: eight participants (Van Leeuwen et al., 2017), 20 participants (Krause & Bengler, 2012), 32 participants (Palinko et al., 2010) and 44 participants (Karl et al., 2013). However, none of these studies used a longitudinal study design; hence, while the final total of 17 is at the lower end of the studies reviewed here, the five-day study design makes this study unique, and for an initial study into information usage the participant sample size was considered justified.

7.2.3. Materials

The creation of the materials formed an important part of the study. First, the information to display to participants was selected, creating multiple challenges in ensuring that there is a rational number of information types that are displayed to the driver. Furthermore, the information displayed should be considered representative of future partially automated vehicles.

After the selection of information, the icons needed to be designed. The challenges here concerned the visual salience of the icons to ensure balanced visual attractiveness (given that eye tracking was used as the measure). Lastly, the driving simulation required the development of a scenario that could present a realistic steady-state driving scenario.

These three challenges will be discussed in this section.

Selection of Information to Display

To derive a justifiable set of information to display in IUS1, the EngD candidate collected information using four different methods:

- First, standards such as BS EN ISO 15008:2017 (BSI, 2017) and ECE 121 (UNECE, 2018) were shortlisted, detailing the minimum information requirements for vehicles today. For example, the vehicle's speed must be displayed at all times on the HMI.
- Information presented in partially automated vehicles available today (for example, Tesla's Autopilot and Cadillac's Super Cruise) were also shortlisted.
- Discussions and collaborative workshops with JLR HMI experts and academics further contributed to the shortlist of information. These discussions were led and organised by the EngD candidate to ensure the information developed would have an industrial relevance and utility to JLR, beyond IUS1&2.
- Results from Scoping Studies 1 & 2 also contributed to the shortlist. For example, the idea of '*knowing what the car will do*' and receiving clear communication of the vehicle's capabilities in '*understandable language*' was a consistent theme in the Scoping Studies. There was difficulty in finding a type of information that could represent these findings from the first two studies; hence, an 'action explanation' information type was developed. Action Explanation would describe in plain language what the vehicle was doing and why.

The result of this process were 30 types of information for presentation inside a partially automated vehicle. However, 30 pieces of information would have been too many to present to participants. Hence, they were then compared against different models of human interaction with information to further shortlist the information. Three models were selected, these were:

1. Skills, Rules, Knowledge (SRK) by Rasmussen (Rasmussen, 1983)
2. Primary, Secondary, Tertiary (PST) by Geiser (Geiser, 1985)
3. Trust model by Choi and Ji (TM) (Choi & Ji, 2015)

The SRK (Rasmussen, 1983) categorised information based on its cognitive demand. For example, a relatively simple type of information would be categorised as Skill-based information. Information that required the driver to interpret then apply an action based on their driving training would be classed as Rule. More complex information that requires the driver to create a mental model of the information and draw comparisons to the real world scenario they are driving in would be classed as Knowledge-based behaviour. The limitation with this model is that different levels of cognitive workload can experienced by different drivers. Particular information may be classed as Skill-based by one driver, but Rule by another; attributed in the literature to the difficulty of placing information into three discrete categories (Dougherty, 1990; Kirwan, 2017; K. J. Vicente & Rasmussen, 1988). For this reason, information was categorised against another model.

The PST (Geiser, 1985) categorised information based on its role in the driving task. Primary information related to the control and manoeuvring of the vehicle. Secondary information allows related to supporting the safe use of the vehicle. Tertiary information is more experiential and desired by drivers, but not crucial to the use of the vehicle. The issue with this model is that it was initially intended for vehicles with little to no automated capability, making some information specific to automated vehicles challenging to categorise.

Finally, the TM (Choi & Ji, 2015) categorised information based on three factors that influence trust: Systems Transparency, Technical Competence and Situation Management. System Transparency information is related to the future state of the vehicle, describing what the vehicle is going to do. Technical Competence confirms the current state of the vehicle. Situation Management deals with information that helps the user understand how they can take over control from the vehicle. In this particular study, because the focus was on steady-state driving and there was only one method in which participants could take back control (by actively using the steering wheel and pedals) situation management was not applicable.

The categorisation of the 30 types of information was accomplished through collaborations with academic and industrial mentors. Nine types of information were represented by all three models and were selected for presentation for the study.

Table 10 below shows each of the nine types of information, along with their icon (the design of which will be detailed in the section following this), a brief description of what the information provided to participants and its categorisation into each of the three models. Table 11 shows the varying information states for each of the information types. Some icons varied continuously in response to the vehicle's states (for example, energy usage and battery level), hence only one of the states is shown.

TABLE 10 INFORMATION FOR IUS1 & 2 HMI (FROM COLLABORATIVE WORKSHOPS WITH ACADEMIC AND INDUSTRIAL PROFESSIONALS). WHERE SK=SKILLS, RU= RULES, KNO=KNOWLEDGE; P=PRIMARY, S=SECONDARY, T=TERTIARY; TC= TECHNICAL COMPETENCE AND ST= SYSTEM TRANSPARENCY

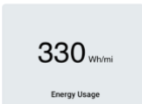
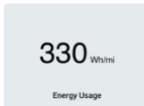
Information	Icon	Description	Category
Action Explanation		Described the vehicle's actions in a descriptive statement	Ru/P/TC
Auto Indicator		Indicated whether partial automated was active	Sk/P/TC
Battery		Indicated the level of charge left in the vehicle's battery	Ru/S/TC
Energy Usage		Indicated the energy use of the vehicle.	Kno/T/TC
Hazard Scanner		Allowed driver to confirm the accuracy of the vehicle's sensing capabilities	Kno/P/ST
Navigation		Indicated the route the vehicle was following and its next manoeuvre.	Sk/T/ST
Road Signs		Would present the last read road sign. Allowed the driver to confirm the vehicle's sensing capabilities	Ru/S/ST
Traffic		Presented the traffic level the vehicle was approaching.	Sk/T/ST
Vehicle Warnings		Would indicate when any issues with the vehicle or hazards in the roadway were detected	Kno/S/TC

TABLE 11 INFORMATION STATES DURING TRIALS FOR IUS1 (ALSO APPLICABLE TO IUS2)

Information	Icon
Action Explanation	
Auto Indicator	
Battery	
Energy Usage	
Hazard Scanner	
Navigation	
Road Signs	
Traffic	
Vehicle Warnings	

HMI Design

Next, the individual icons were designed. Icons were designed using Sketch for Mac (version 52.6), exported as .PNG files and animated into an HMI in Hype 3 for Mac. The challenge was ensuring the icons balanced in terms of visual salience.

Visual salience is the property of an element in vision being more attractive and demanding of a user's visual attention than others (Yantis, 2005). The property of visual salience is less about the specific attributes of an icon or object (such as size or colour) and more about its relative similarities or dissimilarities to the other objects also in view (Barras & Kerzel, 2017; S. I. Becker et al., 2014). For example, a large mountain in the context of a small village would be highly salient; however, the same mountain in the context of another mountain range would not be as visually salient. The implication on HMIs is that using a bolder colour may not necessarily mean that the icon is more visually salient than the others, if the other icons are similarly designed.

Tachistoscopic presentation was used for prototyping the HMI that was presented to participants. The process involved flashing the HMI to testers for a length of 200ms. Each time the HMI was flashed, the information types were presented in different locations. Using the SMI eye-tracking glasses, the fixations to the prototypes were measured to understand if any icons were more visually salient. In response to the results, the Hazard Scanner was redesigned from using a photorealistic vehicle to a generic red arrow.

It is important to note that visual salience is not only a property of the image, but also of the individual observer, making designing for balanced visual salience challenging (De Haas et al., 2019). Hence, by using the unique five-day longitudinal design of this study, it was expected that any remaining visual saliency imbalances would be mitigated. Figure 29 below shows one of the final HMIs presented to participants in the study (note, that this is one configuration of the study and the arrangement of the icons changed for every simulation session).

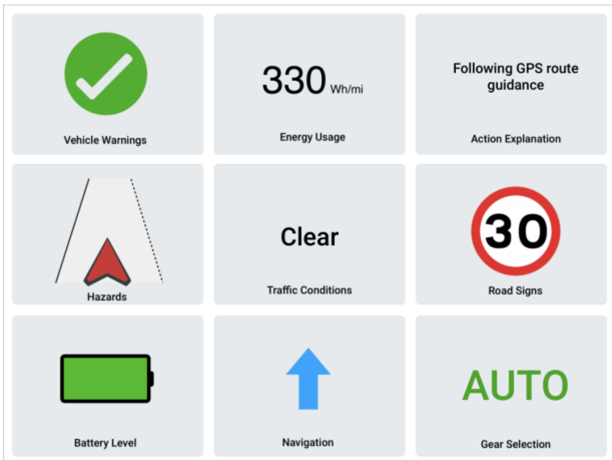


FIGURE 29 FINAL HMI PRESENTED TO PARTICIPANTS FOR IUS1

The HMI was animated in real-time according to the simulated conditions on the road.

Driving Simulations

The majority of a driver's time in an automated vehicle is likely to be uneventful and largely consist of non-emergency scenarios. According to the World Health Organization, road traffic accidents in the UK averaged less than 3 per 100,000 people (WHO, 2018). If a similar rate is assumed for partially automated vehicles, it is justifiable to assume that most of the time will be spent in non-emergency scenarios. Drivers will be asked to monitor these partially automated systems for periods of time which are likely to be uneventful and monotonous – increasing the risk of a driver failing to appropriately monitor the vehicle as a result of boredom (Park et al., 2019). Further, the likely benefits of an automated system are typically only realized in non-critical conditions (Kaber & Endsley, 2004; Martens & Van Den Beukel, 2013), so it is important to the design of future HMI that these steady state scenarios are carefully considered. Most notably, to date, there is a dearth of literature considering how HMIs for partially automated vehicles should consider these continuous steady state portions of driving.

The driving simulation featured steady-state driving across a range of different road types: moving from a residential area to a dual carriageway, motorway then ending on a single carriageway. To add realism, three conflict scenarios were included, but these required no intervention from the driver (though participants would not have been aware of this fact). These were a pedestrian crossing the road, an overtake on the motorway, and an overtake on a single carriageway.

To replicate a steady-state drive, such as a regular commute to work, the road layout was kept the consistent for every simulated session but with variances in the traffic density and the types of vehicles on the road.

For this study, the Dev Sim was used. The details of this setup can be found in section 3.1.

Apparatus

This final selection of nine information types was presented on an iPad Pro 2018 with a 2224 by 1668 pixel 10.5-inch display. SMI eye-tracking glasses were used and recorded the number of fixations to each information type at 30Hz. Glasses were chosen as opposed to fixed, mounted eye trackers as they allowed participants the freedom of movement to turn their head as they would inside a vehicle.

7.2.4. Procedure

The procedure for the study is detailed below:

1. Participants were invited into the WMG Dev Sim and informed consent was taken
2. Participants were instructed to observe the partially automated vehicle operating and use the information presented on the iPad surrogate display in any way they felt was appropriate
3. Participants were fitted with SMI glasses 2.0 and these were calibrated before every session (hence were calibrated twice per day). The calibration process involved asking the participant to fixate on the corners of the iPad surrogate display in turn and clicking a calibrate button on the eye-tracking software for each point.
4. Between simulations, participants were given a five-minute break and offered refreshments.
5. After the second simulation session, participants were then offered a time for the next session on the following day (if not already agreed). Study times for each participant were kept consistent to prevent any effects from the time of day.

7.3. Data Analysis

This study aimed to classify information requirements for drivers of partially automated vehicles and to understand how these change over time with increasing exposure to the automated system. Hence, the number of fixations to the iPad surrogate display and the individual information types were recorded. There were three eye tracking fixation variables analysed:

1. The overall percentage of time participants spent fixating on the iPad surrogate display. All fixations to the display were summated for each participant and this was averaged for the participant population size.
2. Overall number of fixations to each information type. This was calculated by summing the total number of fixations to each information type and averaging for the number of participants.
3. The number of fixations to each information type for each day of the trial week. This allowed the analysis of how information fixations changed over the week. Trends could be observed by analysing the difference between the start and end of the week.

Where data was normally distributed, the Repeated Measures ANOVA was used to test for significant differences in means.

7.4. Results

This section presents the results from the five-day study design and the data analysis that followed.

7.4.1. Overall Percentage of Time Fixating on the Surrogate iPad Display

Below, Table 12 shows the proportion of time that participants on average spent looking at the surrogate iPad display in total.

TABLE 12 OVERALL PERCENTAGE OF TIME FIXATING ON THE INFORMATION DISPLAY FOR IUS1

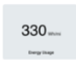
Day	Day 1	Day 2	Day 3	Day 4	Day 5
Proportion of time (%)	2.8	2.0	2.2	1.8	1.7

The total proportion of time participants spent looking at the display fell from 2.8% from Day 1 to 1.7% on Day 5. A Repeated-Measures ANOVA with a Greenhouse-Geiser correction reported that there was no significant difference between the percentages for each day of the trial ($F(1.322, 21.144) = 0.534$, $p > 0.05$).

7.4.2. Overall Fixations to each of the Information types

Below Table 13 shows the average number of fixations to each information type across the whole trial week. The average single fixation is also shown, which is the average length of time a participant spent looking at each information type in a single fixation.

TABLE 13 AVERAGE TOTAL FIXATIONS FOR EACH INFORMATION TYPE IN IUS1

Information	Icon	Average fixations for the whole week per participant	Average single fixation (s)
Action Explanation		41.6	0.3
Auto Indicator		14.3	0.3
Battery		13.0	0.3
Energy Usage		31.2	0.3
Hazard Scanner		40.4	0.3
Navigation		23.8	0.3
Road Signs		20.2	0.3
Traffic		18.7	0.3
Vehicle Warnings		26.2	0.3

Action Explanation had the highest average fixations (*M*=41.6), followed by the Hazard Sensor (*M*=40.4). Battery was the least fixation information (*M*=13.0).

A Repeated-Measures ANOVA with a Greenhouse-Geiser correction reported a significant difference between the mean total fixations for the information types ($F(3.053, 48.844) = 4.585$, $p < 0.05$).

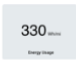
Post hoc tests using the Bonferroni correction found that the average fixations to the Action Explanation and Hazard Scanner were both significantly greater than fixations to Battery ($p= 0.026$ and $p= 0.042$ respectively). Differences in mean fixations between the other information were reported to be non-significant ($p > 0.05$), indicating that Action Explanation and Hazard Scanner had significantly more fixations than the Battery, but not compared to any other information.

All single fixations were 0.3 seconds long (to 1 d.p.). A Repeated-Measures ANOVA with a Greenhouse-Geiser correction reported no significant difference between the average single fixation durations for each information ($F(3.324, 53.186) = 0.947$, $p > 0.05$). This meant that there was no difference in the length of a participant's individual fixation between each of the information types.

7.4.3. Change in Fixations

Below, Table 14 shows the average number of fixations to each information type for each day of the trial week.

TABLE 14 AVERAGE FIXATIONS TO EACH INFORMATION TYPE FOR EACH TRIAL DAY FOR IUS1

Information	Icon	Day 1	Day 2	Day 3	Day 4	Day 5
Action Explanation		13.8	5.4	3.2	7.4	11.7
Auto Indicator		1.0	1.3	3.1	2.2	6.4
Battery		3.1	0.1	1.9	4.5	3.2
Energy Usage		12.9	6.4	7.4	1.4	2.9
Hazard Scanner		6.9	16.4	11.0	3.1	2.9
Navigation		2.0	2.5	9.1	8.2	1.8
Road Signs		2.8	5.2	6.1	4.5	1.4
Traffic		5.9	1.3	3.1	4.7	3.4
Vehicle Warnings		12.4	4.9	2.0	3.4	3.5

A significant effect on the information types fixations by the trial day ($F(2.915, 46.645) = 3.033$, $p < 0.05$) was found. This meant that there was a significant difference in the fixations between the trial days in the study.

Information types that dropped in overall fixations by the end of the week, dropped in fixations after either day 2 or 3:

- Navigation (*M_day3*= 9.1 vs. *M_day5*= 1.8, *p*= 0.003)
- Hazard Sensor (*M_day2*= 16.4 vs. *M_day5*= 2.9, *p*= 0.010)

Some information showed no statistically significant changes overall:

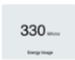
- Vehicle Warnings: between any of the days ($p > 0.05$)
- Energy Usage: between any of the days ($p > 0.05$)
- Road Signs: between any of the days ($p > 0.05$)
- Battery: between any of the days ($p > 0.05$)
- Traffic Conditions displayed a significant drop (*M_day1*= 5.9 vs. *M_day2*= 1.3, *p*= 0.000) then a significant increase (*M_day2*= 1.3 vs. *M_day4*= 4.7, *p*= 0.037).
- Action Explanation displayed a significant drop (*M_day1*= 13.8 vs. *M_day3*= 3.2, *p*= 0.015), then a significant increase (*M_day3*= 3.2 vs. *M_day5*= 11.7, *p*= 0.002).

Hence both Traffic Conditions and Action Explanation were considered as having no overall change in fixations.

The remaining Automated Driving Indicator (*M_day1*= 1.0 vs *M_day5*= 6.4, *p*= 0.007) showed a significant increase in fixations towards the end of the week.

A summary of all the eye-tracking results and their fixation trends can be seen below in Table 15.

TABLE 15 FIXATION CHANGES FOR STEADY STATE DRIVING FOR IUS1

Information	Icon	Summary of Overall Fixation Trends
Action Explanation		No significant change overall
Auto Indicator		Significant increase overall (*M_day1*= 1.0 vs. *M_day5*= 6.4, *p*= 0.007)
Battery		No significant change overall
Energy Usage		No significant change overall
Hazard Scanner		Significant decrease overall (*M_day2*= 16.4 vs. *M_day5*= 2.9, *p*= 0.010)
Navigation		Significant decrease overall (*M_day3*= 9.1 vs. *M_day5*= 1.8, *p*= 0.003)
Road Signs		No significant change overall
Traffic		No significant change overall
Vehicle Warnings		No significant change overall

When the fixation results were organised back into the SRK (Rasmussen, 1983) and PST (Geiser, 1985), there were no clear trends in the categorisation of information. When organised back into the TM (Choi & Ji, 2015), information categorised as System Transparency either remained consistent in fixations or decrease significantly; whereas Technical Competence information either remained consistent in fixations or increased significantly. The organisation back into the TM can be seen below in Table 16.

TABLE 16 FIXATION CHANGES ORGANISED AS THE TRUST MODEL BY CHOI AND JI (2015) FOR IUS1

Information	System Transparency	Technical Competence
Usage Increased		
Usage consistent		
Usage Decreased		

7.5. Discussion

This study aimed to classify the information usage for drivers of partially automated vehicles during steady-state driving and how these requirements changed as a driver became more familiar with the partially automated system.

There are two ways in which the data can be interpreted to contribute towards an adaptive HMI design. The first is based on the eye-mind assumption, that any information that decreased in fixations during steady-state driving should be considered of less importance and should consequently be reduced in prominence on the HMI. The second method is to recognise the importance of some information to the safe use of a partially automated system and to use the reduction in fixations as an indicate that careful thought must be given to how the information can be redesigned to maintain a driver’s attention.

This highlights the methodological benefit of a longitudinal study design again as it provides a broader context to understand the results. The overall results can contribute to understanding what the key information types were, to understand what is important to safety. The fixation trends reveal how information usage changes, to either adapt the information accordingly or reconsider its presentation to drivers to maintain its use.

The combination of the study’s four objectives allows for the classification of the information usage to begin to understand how information usage changes over time in a partially automated vehicle and to inform the design of an adaptive HMI.

7.5.1. Key Results

Overall, fixations to the surrogate information display did not change significantly despite falling from 2.8% on day 1 to 1.7% on day 5.

The Action Explanation (*M*= 41.6) and Hazard Scanner (*M*= 40.4) had significantly more fixations than the Battery (*M*= 13.0) but not compared to any other information. Furthermore, the average single duration of a fixation showed no statistically significant differences and was in line with previous studies (S. A. Birrell & Fowkes, 2014).

There was a significant effect found on the information usage from the day ($F(2.915, 46.645) = 3.033$, $p < 0.05$) and was illustrated when the information was organised back into the TM. System Transparency information was found to remain consistent or decrease significantly in usage. Technical Competence was found to remain consistent or increase significantly in usage.

7.5.2. Overall Percentage of Time Fixating on Information Display

The proportion of time participants spent fixating on the information display as a whole ranged from 2.8% to 1.7%, which is comparable to previous eye-tracking studies which have reported figures such as 4.3% (S. A. Birrell & Fowkes, 2014) to 11.24% (Weinberg et al., 2011).

These previous studies used a manual driving task, not an automated vehicle, and it is notable that the overall percentage of time fixating on the information display in a partially automated vehicle is less than for manually driven vehicles. This may be problematic for future HMIs, as the information display can provide information that can support the driver in the appropriate use of the system (Choi & Ji, 2015). This exacerbates the challenge of ensuring drivers receive the appropriate information because of the more constrained number of fixations. Furthermore, there are no agreed figures for much of a driver's time should be spent monitoring the information that's presented to them. IUS1: Steady State's results suggest that it is important that the HMI quickly communicates key information during the limited number of fixations given by the driver. Adaptive HMIs can provide a solution by giving a higher prominence to certain information, maximising the benefit for a driver when they do fixate on the display. Hence, the next section begins to identify the information that participants fixated on the most.

7.5.3. Overall Fixations to Information types

To reiterate, these results can only apply to steady-state driving, and it is likely that during specific driving scenarios, certain information types will become more important than others. For example, if the vehicle's battery is low, then it is likely that the Battery icon will become more important to the driver. However, as continuous steady-state driving is the likely state that most partially automated driving will operate in, this study sought to classify information usage for this specific scenario.

The key findings from this study is the importance of the Action Explanation information. Previous studies have found that drivers require clear communication of the vehicle's capabilities (Ulahannan et al., 2019). Furthermore, the explanation of what the vehicle is doing, and a reason as to why it is doing that action was also found to be effective in improving the driver's performance with an automated vehicle after handover (Koo et al., 2015; Körber et al., 2018). The results from this study appear to confirm this, with participants fixating on information that was able to provide them with an explanation as to what the vehicle was doing and why. This is a significant result, because to date, there are no other partially automated HMIs, either on the market or coming to the market, that provides this kind of information to the driver. The results indicate that as discovered in previous studies, this information is important to users in order to help them understand the capabilities of the partially automated system.

Alternatively, the high number of fixations may be because of its text-based design, meaning participants had to spend a longer time on the icon to read it. However, the insignificant differences in the average single fixation durations would suggest that the prototyping of the information types was successful and that the text-based design did not have an impact on how long participants took to interpret the information.

The second most fixated on information was the Hazard Scanner. This was future state information that depicted what the vehicle's sensors could see so that the driver can confirm the vehicle's intended actions. This again relates to the need for drivers to understand what the vehicle is doing, although this information did not explain why. Conversely, the Battery was the least fixated on information, though this was expected as the battery level of the vehicle was never an issue during the simulation. Further, the consequences of the vehicle depleting its battery are not as serious in a simulation as in the real world.

There is a suggestion that the Battery is the least important information type when considering just the overall fixations. However, up to this point in the analysis, only the overall fixations have been considered. This study's unique longitudinal design allowed the changes in fixations to be studied, giving the fixation data a greater depth to understand how information usage changes over time.

7.5.4. Change in Information Fixations

The longitudinal design better reflects the real-world interaction with an HMI with these results would suggesting that studies using only a single exposure design are arguably not representative of a driver's true interaction with an HMI.

To summarise the results, first, the Automated Driving Indicator significantly increased in fixations, suggesting that as drivers become more familiar with the partially automated system, that a simple confirmation of the vehicle's technical competence was enough for them to use the system. The Hazard Scanner displayed a significant reduction in fixations, though the overall fixations remained the second-highest for the week. The design of the icon was intended to replicate as much of the functionality as the equivalent information that would be presented in today's partially automated vehicle HMIs. The results would indicate that the Hazard Scanner icon should begin as prominent but reduce in prominence over time. Similarly, Navigation also displayed a significant reduction in fixations. The study indicated that participants tended towards being less concerned with the future state of the vehicle and were content with a confirmation that the vehicle was operating correctly.

There are several implications from these usage trends. The Hazard Scanner and Navigation represent important information types that allow the driver to confirm the vehicle's future actions. What this study has shown has confirmed the issues present in partially automated vehicles today; that drivers tend to use information that is important to the safe use of the vehicle less. This trend is understandable; during continuous steady-state driving, there are no events that require the participant to use future state information. The combination of the steady-state driving scenario and the simulated environment may have inspired participants to take on less responsibility to act on future state information.

Given that continuous steady-state driving is the perceived use case of partially automated vehicles, this study provides a valuable contribution is quantitatively showing how the change in information usage can cause challenges for the monitoring task. Hence, the results would suggest that careful consideration must be given to the design of System Transparency information so that drivers remain in the loop and engaged with the information presented. How this can be achieved is then a design challenge, but the understanding and classification of how the information usage changed is an important first step in understanding how these future HMIs should be designed.

7.5.5. Comments on the Methodology

Aside from the limitations of using a driving simulator discussed in 3.1, other factors should be considered when discussing the results. The first was the sample size of 17. Though the study used a longitudinal design, meaning each participant provided five hours of eye-tracking data in total, it would be important to increase the sample size to consider the results generalisable.

The length of the study was five days and was selected given there were no comparable previous studies. This study was the first to investigate information requirements longitudinally over time. The significant trends observed is a strong indication that this design was an improvement over existing single exposure studies. Rather than being a limitation of this work, this represents an important methodological contribution.

While the study design could always be longer, given that this study was the first of its kind, the methodological contribution of this study is important and while the results are not yet ready to be directly translated into a vehicle's HMI, it has provided an important first understanding of how information usage changes with increased familiarity.

After reflecting on the statistical differences between the days, it may be the case that changes in fixations is more dependent on the number of simulations, rather than the number of days. Furthermore, the one hour time slot for each session was generally too long and most participants finished with around 15 minutes to spare. However, there were occasions that calibration took longer than expected and the full hour was used. The extra time gave more float time to ensure that the schedule for the day ran on time and participants were not kept waiting.

The use of the SMI eye-tracking glasses was successful. Calibrations were almost always successful on the first attempt. The main issue with the SMI system centred around the outdated software that required the use of a laptop running Windows XP. Lagging software optimisations made the use of the software cumbersome but did not affect the quality of the results.

7.6. Conclusions

Information Usage Study 1: Steady State aimed to classify the information usage for drivers of partially automated vehicles and understand how the usage changed over time with increasing familiarity with the system. It is the first study in this doctorate to quantitatively address the question of understanding what information drivers use inside the vehicle. To achieve this, three metrics were recorded: the overall fixations to the information display, the overall fixations to each information type on the display and the change in fixations over the trial week. By analysing all three, conclusions were drawn about how information usage changed inside the partially automated vehicle as the driver became more familiar with the system.

Quantifying the steady-state usage has led to the discovery of important information usage trends that will define how HMIs should adapt as a driver becomes more familiar with the partially automated vehicle. The main finding was that future state information (System Transparency) generally became less used as participants tended towards using information confirming the Technical Competence of the vehicle. This trend raises questions for how System Transparency can be designed as it is important in ensuring the safe use of the vehicle. With the study adopting a continuous steady-state scenario, it was understandable why participants did not require information that would enable them to act pre-emptively, as there was never a scenario the vehicle could not handle. However, by understanding and characterising the change in information usage, HMI designers can take these findings and ensure future HMIs can support and adapt accordingly.

This study also found that the explanation of what the vehicle was doing and why was the most used information type (Action Explanation), confirming participant and attendees' preferences from Scoping Studies 1 & 2. This information is notably missing on all HMIs inside partially automated vehicles, indicating a large deficiency in the HMIs that are currently deployed.

With the information usage being classified for steady-state driving, it was important then to consider the impact of more critical events such as handover. This was the goal for the Information Usage Study 2.

8. Information Usage Study 2: Handover Events

With information usage being classified for steady state driving, it was of interest to understand how this changed when the vehicle was not able to handle all driving conditions and initiated handover. This was also an opportunity to expand on the previous Information Usage Study 1. First, a participant sample size of 27 was achieved- larger than the previous study. Handover events were introduced on three of the nine scenarios. Next, the design was altered to be three days long to allow for greater flexibility of participant scheduling, whilst delivering the same number of simulations. Newer eye tracking was also acquired and deployed for this study. Results were generally analogous between the two studies, with Action Explanation being the most fixated on information type again. Driving handover events also showed clear trends towards specific information types, such as Action Explanation which was consistently paired with Vehicle Warnings. These two Information Usage studies together present the most comprehensive look into information usage in partially automated vehicles to date.

Publications

Ulahannan, A., Birrell, S., Jennings, P and Thompson, S. 2019 Designing an Adaptive Interface: How Information Usage changes following Handover and Warning Evens in a Partially Automated Vehicle. In IEEE Access **[Drafted]**

Information Usage Study 1: Steady State provided an in-depth look into information usage during steady-state driving. The goal was to expand on this through the addition of handover events, requiring the participant to take control of the vehicle. The study provided data for both steady state before handover occurred and after each driving event (two handovers and two warnings). Further, a new eye-tracking system was acquired and used for this study (Tobii Pro 2). Hence there was a stronger contribution to answering *when* information should be presented, in addition to *what*, reflected in Figure 30 below.

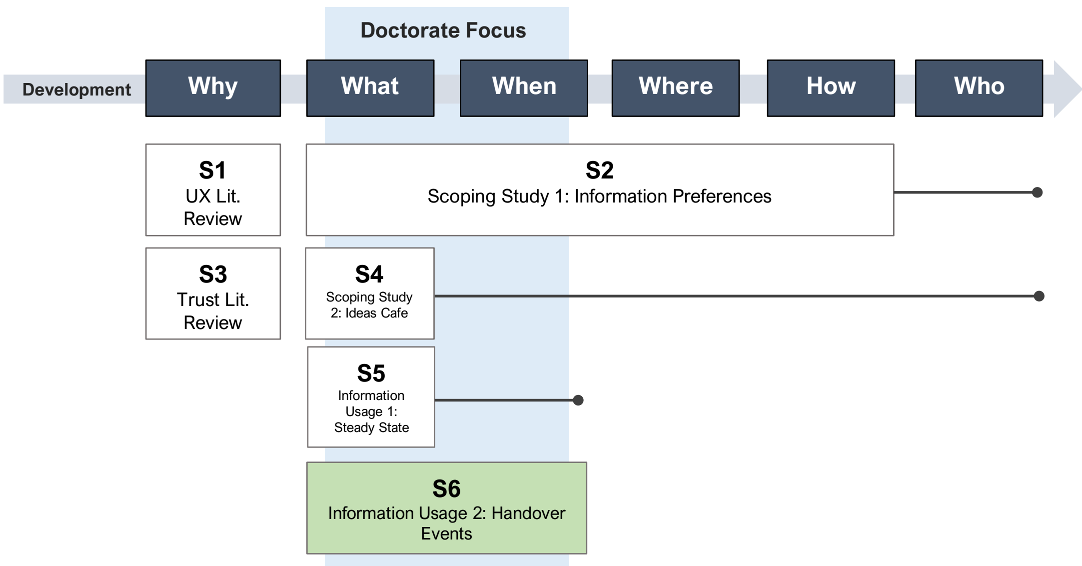


FIGURE 30 DOCTORATE OVERVIEW. SUBMISSION RELEVANT TO THIS SECTION IS HIGHLIGHTED

8.1. Aim & Objectives

8.1.1. Aim

This study aimed to build on IUS1 to develop a more robust classification of information usage in partially automated vehicles, as a driver becomes more familiar with the system.

8.1.2. Objectives

- To measure the overall percentage of time participants spend fixating on the information display
- To measure the change in fixations to each information type as the driver becomes more familiar with the system.
- To measure the change in fixations to each information type after handover events (emergency and planned)
- To measure the change in fixations to each information type after warning events (temperature and handover)
- To compare the steady-state portion of the results to Information Usage Study 1 to develop a more robust classification of how steady state information usage changed with increasing familiarity to a partially automated system.

8.2. Method

FIGURE 31 STUDY OVERVIEW FOR IUS2

An overview of this study can be seen above in Figure 31.

8.2.1. Changes from the First Information Usage Study

There were two key changes from IUS1, required to accommodate the new handover events added. In IUS1, the focus was on steady-state driving; hence, simulations were long (13 minutes long), did not vary in length, and the intention was to understand how familiarity affected information requirements. For these reasons, the five-day design was most appropriate. In this new study, the aim was to understand how information requirements changed during handover and warning scenarios.

Handover Events

The study introduced four events during the study. These were split as two handover events and two warnings. The emergency handover required the participant to take control of the vehicle when warned immediately. The planned handover warning gave notified participants two minutes prior that handover will occur. The planned handover required participants to take control of the vehicle after being warned. The final event was a temperature warning that warned participants that the outside temperature was below four degrees. A summary of the different handover events is shown below in Figure 32.

FIGURE 32 SUMMARY OF HANDOVER EVENTS FOR IUS2

Handover events occurred on three of the nine driving simulations, so participants were not primed to take over control and that the warning was less predictable, in order to simulate real-world partially automated driving scenarios better.

Study Design

The study moved from a five-day design to a three-day design while retaining the same number of driving simulations (nine). This was because the aim of this study was to explore the effect on information usage by the introduction of handover events; it was no longer necessary to test for five days. Furthermore, when analysing the statistical results from IUS1, key changes in fixation behaviour always occurred after day 2 or 3 (Table 15). It became evident that the key factor was not the number of days of exposure, but rather the number of simulations. This raises the possibility of giving all nine simulations to a participant on a single day. However, this was not done to avoid participant fatigue, potential motion sickness and would have negated the longitudinal benefits of the previous study. Consequently, a benefit of the three-day design was that several participants could easily reschedule any experiment timeslots as required. In the previous study, three participants' worth of data was removed from the study because of missed sessions.

The new study design required three simulations a day which was made possible by new eye-tracking glasses from Tobii and upgraded hardware. There were also several optimisations made to the simulation files to allow for faster loading between trials, such as better placement of computer controlled vehicles to require less memory, reuse of road assets and better path management. All of these improvements were as a result of having developed three years of experience using the XPI simulation software.

Minimum Fixation Threshold

IUS1 used a minimum fixation threshold of 200ms. Recommendations for the minimum fixation threshold range between 50 to 500ms (Section 3.3.1). In response to this, Submission 5 (IUS1) details how the statistical analysis was repeated three times with three minimum fixation thresholds (0, 100 and 200ms). The results found there was no difference in the significant differences between the three minimum thresholds; hence, the more stringent fixation threshold was taken. With Information Usage Study 2 (IUS2) utilising the new, more accurate 100Hz Tobii Pro 2, there was an opportunity to review the minimum fixation threshold used.

IUS2 took place one year after IUS1; hence more updated literature was reviewed and found that fixation thresholds as low as 35ms are long enough for 75% accuracy when reading road signs (Costa et al., 2018). This is a very low fixation limit but suggests that drivers can discern information faster than previously thought. This is corroborated by other studies that have also suggested sub-200ms minimum thresholds, such as 60ms (Müller et al., 2016; A. Olsen, 2012). With specific reference to the Tobii system and the I-VT filter used by the Tobii Pro Lab software, 60ms has been found to be appropriate for data recorded with a high level of accuracy (Saez de Urabain et al., 2015). Given that the Tobii Pro Lab software reported that 98% of gaze samples were recorded, suggesting the data was free from noise, the lower 60ms limit could be employed.

The new threshold makes comparisons to IUS1 more challenging, but the two studies are also methodologically different, with the introduction of handover events in IUS2. The intent was never to compare absolute fixation values, but rather the relative trends and changes in information usage.

8.2.2. Participants

A total of 27 participants took part in the study. A breakdown of the demographics can be seen below in Table 17.

TABLE 17 PARTICIPANT DEMOGRAPHICS FOR IUS2

Information	Number
Gender	14 (Male), 13 (Female)
Age	10 (18-24), 13 (25-34), 1 (41-50), 3 (71-80)

Participants were recruited through advertising around the University of Warwick campus and in the local area around Coventry. Any participant who was over the age of 18 and held a valid UK/EU or International driving licence was permitted to take part in the study. Participants who had to wear glasses were excluded from the study.

Justifications for the sample size in the previous IUS1 (17 participants) were provided in section 7.2.2. Given the previous study's sample size was justified as a result of the longitudinal design employed, this study's expanded sample size of 27 was also considered appropriate.

8.2.3. Study Design

This study used a three-day within-subjects design. Participants experienced three partially automated driving scenarios every day for three consecutive days. The study design can be seen below in Figure 33.

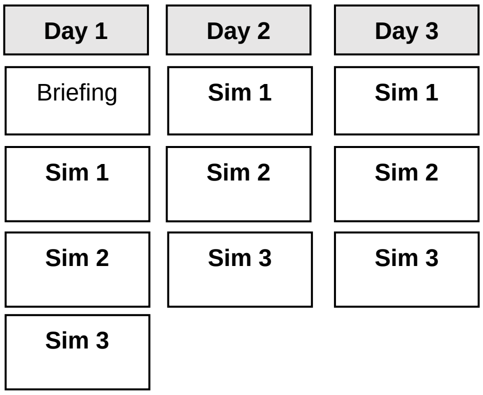


FIGURE 33 STUDY DESIGN FOR IUS2

8.2.4. Driving Simulations

Below in Table 18, all the driving scenarios presented to participants are described.

TABLE 18 DESCRIPTION OF DRIVING SIMULATION SCENARIOS FOR IUS2

Scenario	Description	Duration
Motorway 1	Motorway driving with no handover	8 minutes
Motorway 2	Motorway driving with a planned handover. Warning presented one minute before handover.	8 minutes
Motorway 3	Motorway driving with no handover	9 minutes
Urban 1	Town centre driving with no handover	7 minutes
Urban 2	Town centre driving with heavy traffic	8 minutes
Urban 3	Town centre driving with an outside temperature warning	7 minutes
Rural 1	Rural driving with no handover	5 minutes
Rural 2	Rural driving with no handover	6 minutes
Rural 3	Rural driving with an emergency handover. No prior warning is given.	10 minutes

Only steady-state driving simulations (i.e. with no handovers) were given on day 1 to give participants time acclimatise to the driving simulator environment. The three handover events were randomised for participants across the final two days.

8.2.5. Materials

This study used the same nine information types that were developed for IUS1. Small tweaks were made to the icons, most notably the redesign of the hazard scanner to feature a smaller, blue triangle to represent the participant's vehicle, rather than the large red triangle. This was to bring the design of the icon more in line with the other icons in the HMI. The HMI displayed to participants can be seen below in Figure 34.

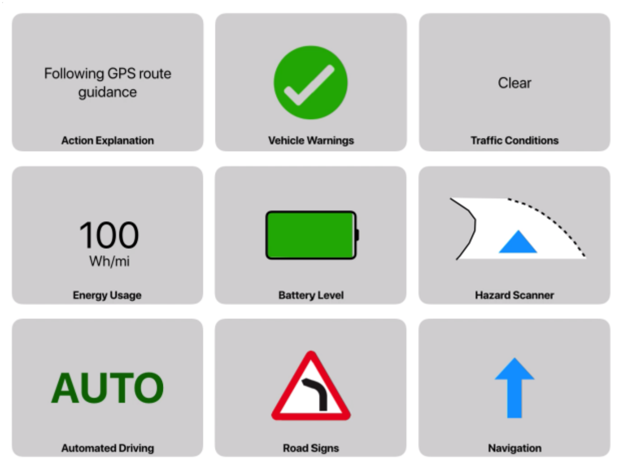


FIGURE 34 FINAL HMI PRESENTED TO PARTICIPANTS FOR IUS2

8.2.6. Apparatus

The study used the same 10.5 inch iPad Pro to display the HMI to the participant and the WMG Dev Sim to display scenarios (Figure 35). The new Tobii Pro Glasses 2 were capable of recording eye tracking data at 100Hz as opposed to the SMI's 30Hz. Furthermore, the Tobii recorded a wider field of view, reducing the risk of the HMI being cropped out of view on the recorded video. The accompanying Tobii Pro Lab software featured new methods of data analysis, such as automatic mapping of eye-tracking data. However, after testing, this feature was not used and all data was manually coded.

FIGURE 35 APPARATUS USED IN IUS2. PICTURED IS THE IPAD PRO, TOBII PRO 2, SURFACE PRO, CALIBRATION CARD, SCREEN CLEANING CLOTH AND BLUETOOTH HEADPHONES USED TO CONTROL INFORMATION DISPLAY PLAYBACK

8.3. Data Analysis

In addressing the aims of the study, there were several different ways the data was analysed using SPSS Statistics 25.0:

1. The overall percentage of time spent fixating on the information display was calculated by summing and calculating the average for the total duration data.
    a. Unlike IUS1, this was done for the entirety of the week rather than for individual days. This is because the presentation of scenarios was randomised meaning individual simulation lengths varied between participants and days.
    b. Normality was checked using the Shapiro-Wilks Test. Consequently, a Repeated-Measures ANOVA was carried out. Post-hoc pairwise comparisons with the Bonferroni correction were used to identify where significant differences occurred.
2. The change in fixations to individual information types during steady-state driving was calculated by taking the number of fixations recorded by the eye-tracking and averaging for individual days.
    a. Normality was checked using the Shapiro-Wilks Test. Consequently, the non-parametric Friedman Test was used to test for significant differences. This was followed by post-hoc Wilcoxon Signed-Ranks Tests.
3. The change in fixations to individual information types during the events was calculated by calculating the percentage change after the event compared to the average fixations during one minute of steady-state driving.
    a. Paired t-tests were used to test for statistically significant differences between the steady-state one minute average and the post-event fixations. The issue of multiple comparisons was addressed by using the Holm-Bonferroni correction.

8.4. Results

This section presents the results from the three-day study design.

8.4.1. Overall Percentage of Time Fixating on the Information Display

Below, Table 19 shows the proportion of time that participants on average spent fixating on the information display.

TABLE 19 OVERALL PERCENTAGE OF TIME FIXATING ON THE INFORMATION DISPLAY IN IUS2

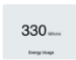
Time Fixating on Information Display	Overall
Proportion of time (%)	3.45

Participants spent 3.45% of the total time of simulation exposure (68 minutes), fixating on the information display.

8.4.2. Overall Fixations to each of the Information types

Below, Table 20 shows the average number of fixations to each information type for the whole trial week. The average single fixation is also shown, which is the average length of time a participant spent fixating on an information type in a single fixation.

TABLE 20 AVERAGE TOTAL FIXATIONS FOR EACH INFORMATION TYPE IN IUS2

Information	Icon	Average fixations for the whole week per participant	Average single fixation (s)
Action Explanation		109	0.18
Auto Indicator		106	0.18
Battery		83.5	0.16
Energy Usage		67.8	0.18
Hazard Scanner		103	0.19
Navigation		98.9	0.17
Road Signs		109	0.17
Traffic		49.1	0.19
Vehicle Warnings		56.1	0.17

Similar to IUS1, Action Explanation was one of the most fixated on information types (*M*= 109). Road Signs also exhibited a high number of fixations (*M*= 109). This was followed by the Auto Indicator (*M*= 106) and Hazard Scanner (*M*= 103). In the IUS1, the Auto Indicator was one of the least fixated on information types, whereas it is one of the most fixated on icons in IUS2. The least fixated on information was Traffic (*M*= 49.1), which had a similarly low total number of fixations in IUS1.

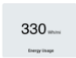
A Repeated-Measures ANOVA with a Greenhouse-Geiser correction reported a significant difference between the mean total fixations to the information types ($F(3.332, 86.830) = 7.210$, $p < 0.05$). Post hoc tests using the Bonferroni correction found that Traffic (*M*= 49.1) and Vehicle Warnings (*M*= 56.1) were significantly less fixated on than Action Explanation (*M*= 109), Battery (*M*= 83.5), Hazard Scanner (*M*= 103), Navigation (*M*= 98.9) and Road Signs (*M*= 109). This indicated that Traffic and Vehicle Warnings were the least fixated on information types for IUS2.

A Repeated-Measures ANOVA with a Greenhouse-Geiser correction reported a significant difference between the average single fixation lengths ($F(4.098, 106.549) = 4.308$, $p < 0.05$). Battery (*sM*= 0.16s) (where *sM*= mean single fixation) attracted significantly shorter single fixations on average than the Hazard Scanner (*sM*= 0.19s), Navigation (*sM*= 0.17) and Traffic (*sM*= 0.19). Action Explanation was found to have no significant differences in average single fixation length compared to the other information types.

8.4.3. Change in Fixations during Steady State

Table 21 below shows the average number of fixations to each information type for each day of the trial week.

TABLE 21 AVERAGE FIXATIONS TO EACH INFORMATION TYPE FOR EACH TRIAL DAY FOR IUS2

Information	Icon	Day 1	Day 2	Day 3	Friedman and Wilcoxon Tests
Action Explanation		13.9	9.80	12.4	$\chi^2(2) = 2.598$, $p > 0.05$
Auto Indicator		16.7	10.1	8.55	**$\chi^2(2) = 12.906$, $p = 0.002$** **Day 1 and Day 2, 3 (p= 0.006, 0.002)**
Battery		12.5	7.68	7.63	**$\chi^2(2) = 10.491$, $p = 0.005$** **Day 1 and Day 2, 3 (p= 0.006, 0.002)**
Energy Usage		9.82	6.19	6.61	**$\chi^2(2) = 15.360$, $p = 0.000$** **Day 1 and 2,3 (p=0.003, 0.008)**
Hazard Scanner		12.3	11.4	10.6	$\chi^2(2) = 2.509$, $p > 0.05$
Navigation		12.1	11.5	9.35	$\chi^2(2) = 4.514$, $p > 0.05$
Road Signs		17.2	9.88	9.16	**$\chi^2(2) = 18.250$, $p = 0.000$** **Day 1 and 2, 3 (p= 0.001, 0.000)**
Traffic		6.20	4.92	5.27	$\chi^2(2) = 1.390$, $p > 0.05$
Vehicle Warnings		7.99	5.74	4.96	$\chi^2(2) = 3.185$, $p > 0.05$

Data for the individual days of fixation data was not normally distributed. Significant differences in the fixation counts between the days was observed. In all cases where a significance was reported, Day 1 was always significantly different from the other days. Across all information types, there was no significant difference between Day 2 and 3.

The largest decrease in fixations between day 1 and 3 was noted for the automated indicator (*M_day1* = 16.7, *M_day3* = 8.6, p=0.002) and road signs (*M_day1* = 17.2, *M_day3* = 9.16, p = 0.000). Action Explanation, Hazard Scanner, Navigation, Traffic and Vehicle Warnings all displayed no significant differences in fixation counts across the trial week.

The fixation changes were then organised back into the TM as was done in IUS1, shown below in Table 22.

TABLE 22 FIXATION CHANGES FOR STEADY STATE DRIVING FOR IUS2

Information	System Transparency	Technical Competence
Usage Increased		
Usage consistent		
Usage Decreased		

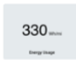
No information displayed a significant increase and that it was information concerning the Technical Competence of the vehicle that generally less used by participants, whereas System Transparency information remained largely consistent in usage.

8.4.4. Change in Fixations after Handover Events

Table 23 below shows the change in fixations after each event, of which two were handover events and two were warning events. The event is listed in the left-most column. The average steady-state fixations for one minute are listed along the top row. For each event, the average number of fixations and the percentage change in fixations when compared to steady-state is reported.

The statistical analyses run on the data in this section focussed on any significant differences between the pre- and post-event (2 handover and 2 warnings events) average fixations to each individual information type.

TABLE 23 CHANGE IN FIXATIONS AFTER EACH HANDOVER EVENT

Info.	Action Exp.	Auto Indic.	Batt.	Ener.	Haz. Scan.	Nav.	Road Signs	Traffic	Vehic. Warn.
Icon									
Steady State 1 min. avg. (ss)	2.35	2.29	1.80	1.47	2.23	2.14	2.36	1.06	1.22
Emerg. Handover (eh)	7.00	1.22	1.33	1.37	1.26	0.81	0.37	0.30	3.44
	+198%	-46.8%	-26.3%	-6.75%	-43.5%	-62.0%	-84.3%	-72.1%	+183%
Planned Handover Warning (phw)	21.96	3.48	3.31	3.31	1.87	2.46	2.31	2.00	21.96
	+834%	+51.4%	+83.2%	+126%	-16.1%	+14.9 %	-2.00%	+88.1 %	+520%
Planned Handover (ph)	3.41	2.63	1.81	1.37	0.81	1.11	2.11	0.48	0.85
	+44.9%	+14.4%	+0.32%	-6.75%	-63.5%	-48.2%	-10.6%	-54.7%	-29.9%
Temp. Warning (tw)	4.48	1.37	2.33	1.56	2.74	3.41	2.44	0.93	3.70
	+90.6%	-40.4%	+29.0%	+5.86 %	+22.9 %	+59.0 %	+3.53 %	-12.9%	205%

After Emergency Handover

In comparison to the average steady state pre-handover fixations, it was found that after the emergency handover event:

- Fixations to Action Explanation increased by 197% ($t(26)= -3.377$ $p = 0.002$)
- Fixations to Automated Indicator decreased by 46.8% ($t(26)= 2.566$ $p = 0.016$)
- Fixations to Battery showed no significant change ($p > 0.05$)
- Fixations to Energy showed no significant change ($p > 0.05$)
- Fixations to Hazard scanner decreased by 43.5% ($t(26)= 2.349$ $p = 0.027$)
- Fixations to Navigation decreased by 62.0% ($t(26)= 3.911$ $p = 0.001$)
- Fixations to Road Signs decreased by 84.3% ($t(26)= 8.254$ $p = 0.000$)
- Fixations to Traffic decreased by 72.1% ($t(26)= 3.679$ $p = 0.001$
- Fixations to Vehicle Warnings increased by 183% ($t(26)= -2.603$ $p = 0.015$).

The results are illustrated below in Figure 36. Results below show the comparison between pre- and post-emergency handover average fixations.

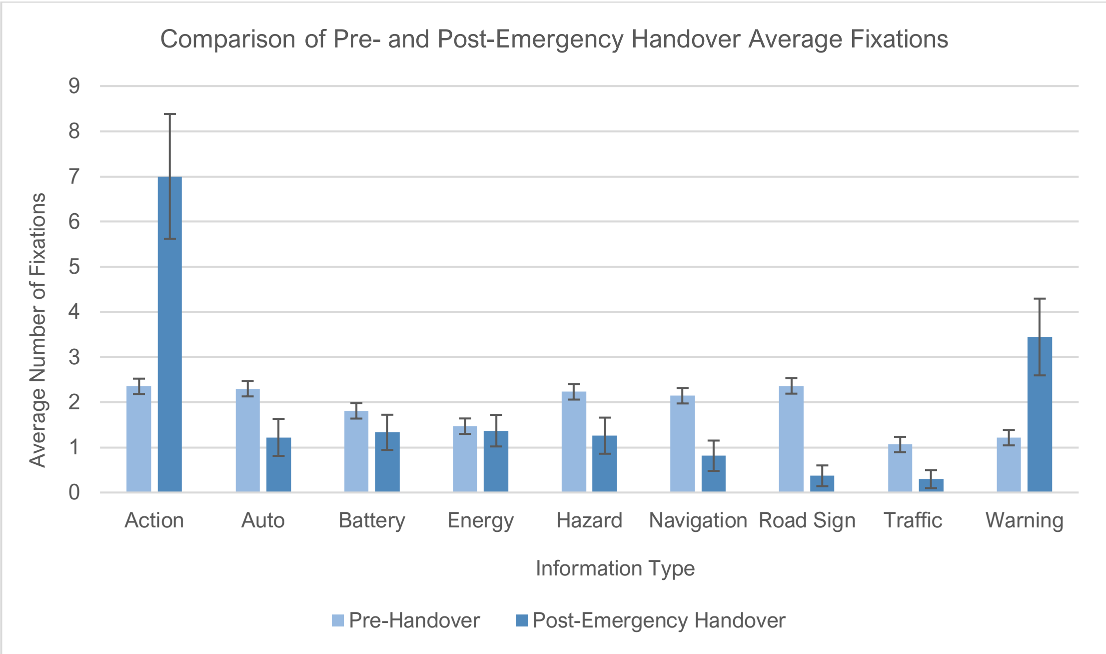


FIGURE 36 COMPARISON OF PRE- AND POST-EMERGENCY HANDOVER AVERAGE FIXATIONS

Below in Table 24, the changes in fixations to the information types were organised back into the TM.

TABLE 24 FIXATION CHANGES AFTER EMERGENCY HANDOVER COMPARED TO THE AVERAGE STEADY STATE

Information	System Transparency	Technical Competence
Usage Increased		
Usage consistent		
Usage Decreased		

After an emergency handover, all System Transparency information decreased significantly in usage. Technical Competence information had more diverse results, with Action Explanation pairing with Vehicle Warnings when increasing in fixations. Battery and Energy both remained consistent. Auto Indicator fell in fixations.

After Planned Handover Warning

In comparison to the average steady state pre-handover fixations, it was found that after the planned handover warning event:

- Fixations to Action Explanation increased by 833% ($t(26)$= -9.827 p = 0.000)
- Fixations to Automated Indicator increased by 51.4% ($t(26)$= -2.184 p = 0.038)
- Fixations to Battery increased by 83.2% ($t(26)$= -2.058 p = 0.050)
- Fixations to Energy increased by 126% ($t(26)$= -2.858 p = 0.008)
- Fixations to Hazard Scanner showed no significant change ($p > 0.05$)
- Fixations to Navigation showed no significant change ($p > 0.05$)
- Fixations to Road Signs showed no significant change ($p > 0.05$)
- Fixations to Traffic showed no significant change ($p > 0.05$)
- Fixations to Vehicle Warnings increased by 520% ($t(26)$= -7.565 p = 0.000)

(Note, the period of two minutes was normalised to one minute for this comparison)

The results are illustrated below in Figure 37. Results below show the comparison between pre- and post-handover warning average fixations.

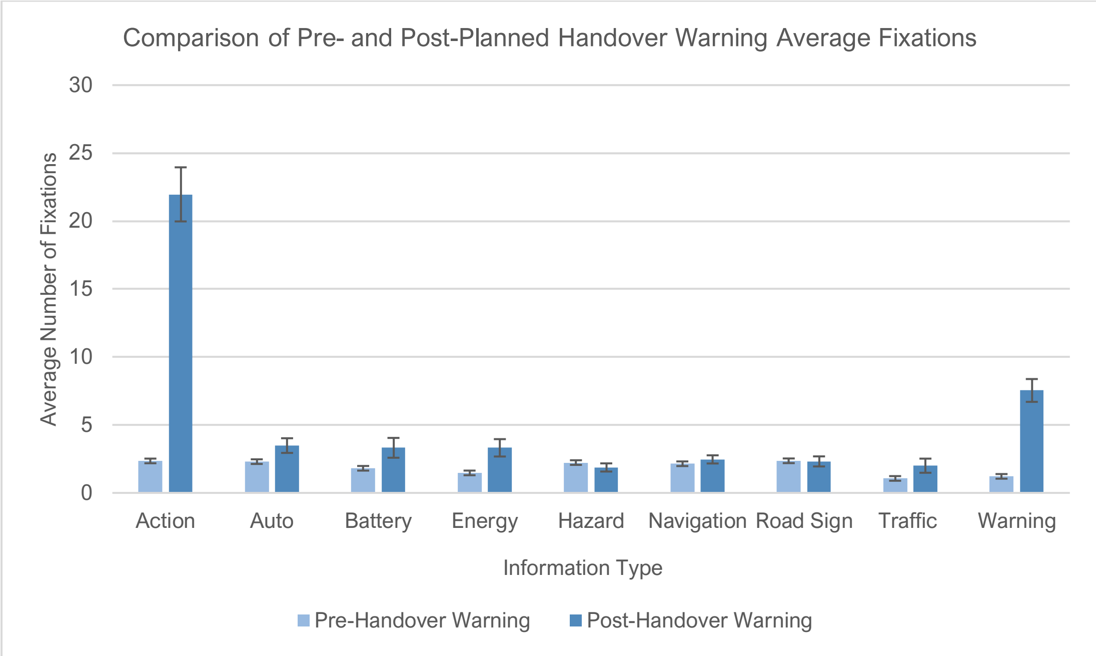


FIGURE 37 COMPARISON OF PRE- AND POST-HANDOVER WARNING AVERAGE FIXATIONS. NOTE, THE PERIOD OF TWO MINUTES WAS NORMALISED TO ONE MINUTE FOR THIS COMPARISON

Below Table 25 shows the changes in fixations to information types after handover warning organised against the TM.

TABLE 25 FIXATION CHANGES AFTER HANDOVER WARNING COMPARED TO THE AVERAGE STEADY STATE

Information	System Transparency	Technical Competence
Usage Increased		
Usage consistent		
Usage Decreased		

After the handover warning participants increased usage of all Technical Competence information, whereas System Transparency remained consistent in usage.

After Planned Handover

In comparison to the average steady state pre-handover fixations, it was found that after the planned handover event:

- Fixations to Action Explanation showed no significant change ($p > 0.05$)
- Fixations to Automated Indicator showed no significant change ($p > 0.05$)
- Fixations to Battery showed no significant change ($p > 0.05$)
- Fixations to Energy showed no significant change ($p > 0.05$)

- Fixations to Hazard Scanner decreased by 63.5% ($t(26) = 4.164$ $p = 0.000$)
- Fixations to Navigation decreased by 48.2% ($t(26) = 3.293$ $p = 0.003$)
- Fixations to Road Signs showed no significant change ($p > 0.05$)
- Fixations to Traffic decreased by 54.7% ($t(26) = 2.848$ $p = 0.008$)
- Fixations to Vehicle Warnings showed no significant change ($p > 0.05$)

The results are illustrated below in Figure 38. Results below show the comparison between pre- and post-planned handover average fixations.

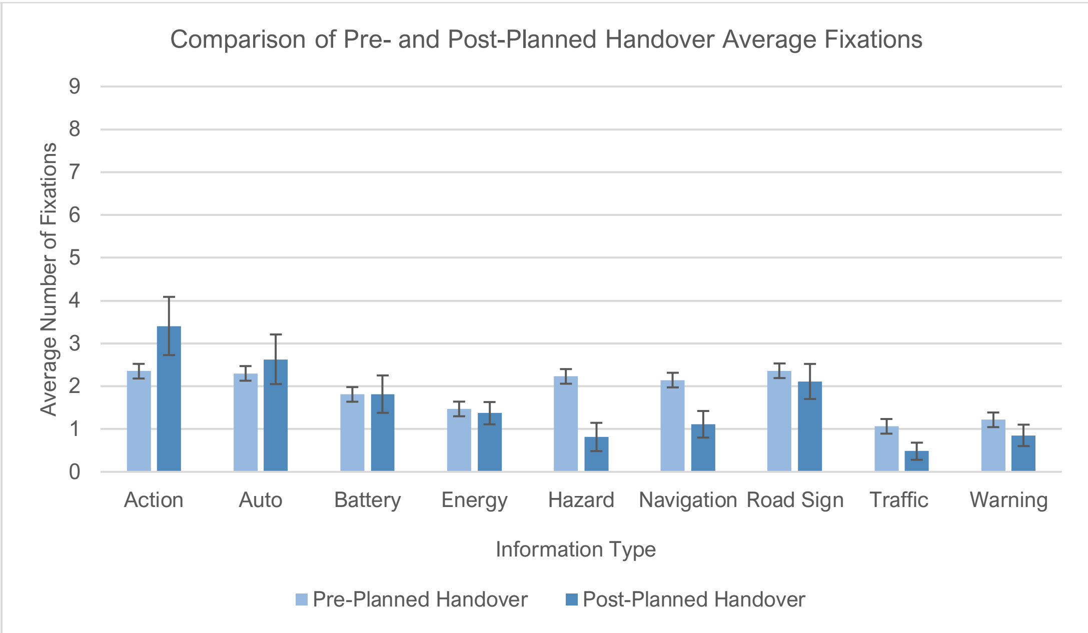


FIGURE 38 COMPARISON OF PRE- AND POST-PLANNED HANDOVER AVERAGE FIXATIONS

Below Table 26 shows the changes in fixations to information types after the planned handover organised against the TM.

TABLE 26 FIXATION CHANGES AFTER PLANNED HANDOVER COMPARED TO THE AVERAGE STEADY STATE

Information	System Transparency	Technical Competence
Usage Increased		
Usage consistent		
Usage Decreased		

After the planned handover, all Technical Competence information remained consistent in usage. Most System Transparency information fell in usage, with the exception of Road Signs.

After Temperature Warning

In comparison to the average steady state pre-handover fixations, it was found that after the temperature warning event:

- Fixations to Action Explanation increased by 90.6% ($t(26) = -3.225$ $p = 0.003$)
- Fixations to Automated Indicator decreased by 40.4% ($t(26) = 3.239$ $p = 0.003$)
- Fixations to Battery showed no significant change ($p > 0.05$)
- Fixations to Energy showed no significant change ($p > 0.05$)
- Fixations to Hazard Scanner showed no significant change ($p > 0.05$)
- Fixations to Navigation increased by 59.0% ($t(26) = -2.517$ $p = 0.018$)
- Fixations to Road Signs showed no significant change ($p > 0.05$)
- Fixations to Traffic showed no significant change ($p > 0.05$)
- Fixations to Vehicle Warnings increased by 205% ($t(26) = -2.990$ $p = 0.006$)

The results are illustrated below in Figure 39. Results below show the comparison between pre- and post-planned temperature warning average fixations.

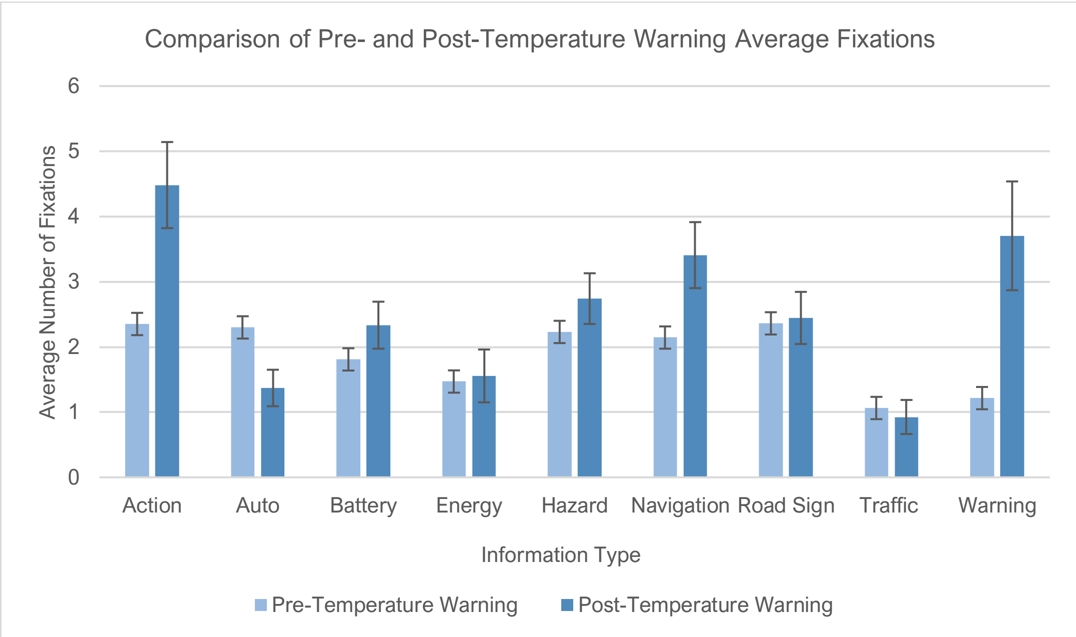


FIGURE 39 COMPARISON OF PRE- AND POST-TMPERATURE WARNING AVERAGE FIXATIONS

Below Table 27 shows the changes in fixations to the information types after the temperature warning organised against the TM.

TABLE 27 FIXATION CHANGES AFTER TEMPERATURE WARNING COMPARED TO THE AVERAGE STEADY STATE

Information	System Transparency	Technical Competence
Usage Increased		
Usage consistent		
Usage Decreased		

Results were varied after the temperature warning. Most System Transparency information remained consistent in usage, with the exception of Navigation. Technical Competence information followed an identical pattern to fixations after the emergency handover event.

8.5. Discussion

This study aimed to build on IUS1 to develop a more robust classification of information usage in partially automated vehicles, as a driver becomes more familiar with the system. To achieve this, the study introduced handover events and a new, more accurate eye-tracking system.

As in IUS1, the eye-mind assumption was used in this study. The discussion of these results required consideration of two aspects: the first being that any information that decreased in fixations should be reduced in prominence on the display or vice versa; the second being a recognition that some information is important to the use of a partially automated system and should also be considered in the wider context of the overall fixations to understand if it should be adapted or not.

8.5.1. Overall Fixations

Overall, participants spent 3.45% of the total simulation time fixating on the information display. In the previous IUS1, the results ranged between 2.87% and 1.75%. As in IUS1, the results found that participants used the information display less during partially automated driving in comparison to manual driving figures previously reported (S. A. Birrell & Fowkes, 2014; Weinberg et al., 2011). The average time spent fixating on the display was higher in IUS2 than IUS1, indicating that the presence of handover events caused participants to spend more time fixating on the information display.

8.5.2. Fixations to Information types

Traffic (*M*= 49.1) and Vehicle Warnings (*M*= 56.1) were generally found to be significantly less fixated on than the other information types. Furthermore, the average single fixation for the action explanation was found to show no significant differences to the other information types.

The Auto Indicator, which displayed a significant increase in IUS1 was found to decrease significantly in fixations in IUS2. This suggested that the introduction of handover events caused participants to use the detailed information more, such as the Hazard Scanner, which was found to remain consistent in fixations throughout IUS2. The two most fixated on information types overall was the Action Explanation and the Road Signs. The Road Signs was one of the least fixated on information types in IUS1 but was one of the highest in IUS2. This change could be attributed to the introduction of handover events, which may have required participants to use information that could help confirm future actions more closely. The Road Signs allowed the participant to quickly confirm if the vehicle had understood the traffic situation it was entering, hence provided a method of confirming the future actions of the vehicle.

Overall, only information concerned with the Technical Competence of the vehicle exhibited a significant decrease throughout the trial sessions. The more varied scenarios (compared to IUS1's consistent steady state layout) may explain the consistent use of System Transparency information (as the future state was less predictable) and the reduction Technical Competence information usage (that was highly fixated on in IUS1's steady state scenarios).

The exception to the overall reduction in the use of Technical Competence information was Action Explanation and Vehicle Warnings, both of which showed no statistically significant change over the trial week. Participants required an explanation as to what the vehicle was doing and why, which was also consistent with preliminary results from other studies (Gold et al., 2015; Koo et al., 2015). Despite Vehicle Warnings having one of the lowest overall fixation counts, the consistent fixations to the information would suggest that it remains of equal importance to users, regardless of their increasing familiarity with the system. These two information types will be discussed in more detail in the following section 8.5.3.

In all cases where a decrease in fixations was observed, the fixations fell significantly after day 1, but there was no further drop between days 2 and 3. Participants appeared quick to adapt to the information presented and settled into a pattern of usage faster than in IUS1, where changes were still observed until the last day. On reflection, it also validates the move from a five-day design to a three-day design. The assumption that the salient factor behind the change in information usage was the number of simulations, not the number of days, was appropriate.

8.5.3. Fixation changes after events

IUS2 presented four events: two handovers and two warning events. In all cases, both Action Explanation and Vehicle Warnings always increased significantly in usage or remained consistent in usage together. It is a strong indication that the HMI must provide drivers with a detailed textual explanation of what the vehicle is doing and why, along with an accompanying visual icon during a driving event. This need for a multi-modal warnings have previously been observed (Politis et al., 2015). Though two visual warnings are not strictly multi-modal as they use the same modality, it is notable that the information types acted as pairs and is an important recommendation for future HMI guidelines.

The other notable pairing was the Battery and Energy Usage, which also changed in fixations after events as a pair. Range anxiety is a significant barrier for the adoption of electric vehicles (S. A. Birrell et al., 2014), so it is understandable that two information types related to the battery capacity of the vehicle to be closely related to each other. It is another important finding for future HMI that if battery information is presented to the user, then accompanying information on the energy usage should also be provided.

After the emergency handover, all System Transparency information reduced significantly in fixations. This implies that for events where immediate action is required from the participant with no prior warning, future state vehicle information becomes less important, with participants favouring Technical Competence information exclusively.

Similarly, after the planned handover, most System Transparency information reduced significantly in fixations (except for Road Signs), whereas all Technical Competence information remained consistent in usage.

A similar trend was also noted after the handover warning event, where System Transparency information remained consistent in usage, but Technical Competence had increased significantly. Drivers wanted to confirm the Technical Competence of the vehicle’s system more after a warning had been received, using information that gives an indication of whether the system is still active or not. That fact that System Transparency information remained consistent indicates the information is still important, but more prominence should be given to information that confirms the vehicle is still in operating in automated mode.

8.6. Conclusion

This study expanded on Information Usage Study 1 by introducing handover events to develop a more robust understanding of how information usage changes inside partially automated vehicles. The results found significant differences in the steady-state information usage and a number of the trends were consistent with IUS1. The Action Explanation information type was the most fixated on in both studies. Furthermore, after all driving events, Action Explanation was found to increase in usage, and the information was always paired with Vehicle Warnings.

Any statistically significant changes in fixations to the information types were only observed after day 1 and not between day 2 and 3, indicating that participants had settled into a pattern of information use. Furthermore, the consistency of information usage suggested the change to the three-day study design was appropriate and the contributing factor to the change in fixations was the number of simulations, not the number of days over which they were tested.

The results from IUS2 can now contribute to a holistic set of design recommendations, comprised of the results from the four studies in this doctorate. For that reason, it was more appropriate to discuss the results of IUS2 2 in tandem with the other studies. The following Section 0 will bring together these results into a synthesised discussion.

9. Design Recommendations

This doctorate aimed to understand how HMIs can more appropriately support the driver in the use of a partially automated Level 2 vehicle system or higher. Four studies were conducted to achieve this. This section now brings together all the results from the four studies in this doctorate to synthesise design guidelines for future partially automated vehicles.

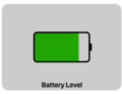
Following these design recommendations, a review of existing HMIs was undertaken. The researcher used photos available from the internet, but also conducted field tests using vehicles available in the competitor fleet at Jaguar Land Rover, in order to review current HMIs inside partially automated vehicles. This can be found in Section 9.2.

Finally, examples of how information could be adapted on a future HMI are presented. These concepts are yet to be validated through user trials but help illustrate the design recommendations made in this Section. This can be found in Section 0

Below, Table 28 details the key results from each of the four studies, along with the implications for the design of future adaptive HMIs.

9.1. Synthesis of Doctorate Results

TABLE 28 SUMMARY OF PRELIMINARY HMI RECOMMENDATIONS [IUS: INFORMATION USAGE STUDY]

Information	HMI Recommendation and Results
 **Action Explanation**	• **Higher prominence during any event** • **High prominence during steady-state** • Requested by participants in Scoping Study 1 • Was an emergent theme from Scoping Study 2 • No significant change in fixations for IUS1&2 • Was significantly more fixated on than other information • Increased usage in all events and was always paired with Vehicle Warnings.
 **Auto Indicator**	• **Appropriate adaption after events** • **Moderate prominence during steady-state** • Requested by participants in Scoping Study 1 • Increased significantly in fixations in IUS1 but had low overall fixations • Decreased significantly in fixations in IUS2, but had high overall fixations • Varied changes in fixations after events
 **Battery Level**	• **Higher prominence during the handover warning** • **Moderate prominence during steady-state** • Requested by attendees in Scoping Study 2 • No statistically significant change in IUS1 but had low overall fixations • Decreased significantly in fixations in IUS 2 but had moderate overall fixations • Increased usage after the planned handover warning and was always paired with Energy Usage
 **Energy Usage**	• **Higher prominence during the handover warning** • **Moderate prominence during steady-state** • Requested by attendees in Scoping Study 2 • No significant change in fixations in IUS1, with moderate overall fixations • Decreased significantly in IUS2, with moderate overall fixations • Increased usage after the planned handover warning and was always paired with Battery
 **Hazard Scanner**	• **Lower prominence after handover events, consistent after warnings** • **High prominence during steady-state** • Requested by participants in Scoping Study 1 • Decreased significantly in IUS1, with high overall fixations • No significant change in fixations in IUS2 with high overall fixations • Lower usage after both handover events
 **Navigation**	• **Lower prominence after handover events and familiar routes** • **High prominence during steady-state in new routes** • Requested by participants in Scoping Study 1 • Decreased significantly in IUS1 with low overall fixations • No significant change in IUS2 with high overall fixations • Lower usage after handover events

Continued on next page

Information	HMI Recommendation and Results
 Road Signs	• **Lower prominence after emergency handover** • **Moderate prominence during steady-state**
	• Requested by participants in Scoping Study 1 • No significant change in fixations in IUS1 with low overall fixations • Decreased significantly in IUS2 with high overall fixations • Consistent usage after planned handover, but decrease after emergency
 Traffic Conditions	• **Lower prominence after handover events, consistent after warnings** • **Low prominence during steady-state**
	• Requested by participants in Scoping Study 1 • No significant change in IUS1 with low overall fixations • No significant change in IUS2 with low overall fixations • Lower usage after handover events
 Vehicle Warnings	• **Higher prominence after events** • **Low prominence during steady-state**
	• No significant change in IUS1 with low overall fixations • No significant change in IUS2 with low overall fixations • Higher usage after emergency handover and both warning events. Consistent after planned handover.

9.1.1. Action Explanation and Vehicle Warnings

Consistently, across both Information Usage Studies, Action Explanation was the most fixated on information type. Vehicle Warnings also displayed very similar usage patterns to Action Explanation, though with a lower overall number of fixations.

The Action Explanation was initially born out of the results from Scoping Studies 1 and 2. Across the two driver groupings from Scoping Study 1, High Information Preference (HIP) and Low Information Preference (LIP); there was a need for the vehicle to communicate its status to the driver. In the case of HIP participants, they wanted richer information concerned with all driving scenarios. In contrast, LIP participants only wanted information in critical scenarios. However, the majority of participants wanted information presented in a visual form only. Hence, the Action Explanation appeared to be a solution to this problem, providing highly detailed information in all scenarios. Furthermore, because it did not require any additional modalities to communicate meaning, it could satisfy a LIP driver too by minimising the amount of information presented to them.

From the Ideas Café, one of the most prevalent themes was the need to understand the vehicle's capabilities in 'understandable language'. Attendees were concerned about the usability of the HMI, "*Should be controllable by all, not just technologists*". By providing an explanation of the vehicle's intentions, these concerns could be addressed.

None of the information types reviewed from standards and existing HMIs described in 7.2.3 described this kind of information. The importance of the information has been demonstrated, not only in the two Information Usage studies, but also through the qualitative data gathered in the Scoping Studies.

This has several important implications for the information required for future adaptive HMIs. The results from this doctorate strongly indicate that a form of Action Explanation is required by drivers of partially automated systems, with this result being consistent across two longitudinal studies. Section 7.5.3 discussed some of the literature that found the explanation of what and why the vehicle is taking certain actions to improve driving performance after handover (Koo et al., 2015; Körber et al., 2018).

The most illustrative result was the significant increase in fixations to Action Explanation after three of the handover events observed in IUS2. After the planned handover warning, fixations to the Action Explanation increased 833%; after the emergency handover, fixations increased by 197% and after the temperature warning, fixations increased by 90.6%; and were all statistically significant increases. Participants were looking for a way to understand why the vehicle had an issue and notably, Action Explanation was always paired with Vehicle Warnings. This suggests that these two information types should be presented and adapted in prominence together. The reasons for this are discussed previously in 8.5.3.

With the exception of the papers by Koo et al. (2015) and Körber, Prasch and Bengler (2018) there is a dearth of research into a similar type of information to Action Explanation. Many parallels can be drawn to research into spoken verbal auditory warnings. In many ways, the Action Explanation represents a textual version of verbal auditory alerts that have been studied before, and this type of information can improve trust and user experience (Du et al., 2019; Forster et al., 2017) and can decrease workload and driver distraction (Naujoks et al., 2016). Results by Du et al. (2019) also suggested that the level of automation (i.e. the SAE levels) has no impact on the effectiveness of providing Action Explanation information, with regards to trust and user acceptance. This means the contribution of this research could be applicable to the higher levels of automation. However, to date, these studies have only considered the auditory form of the information, leaving the research gap into which this doctorate had contributed significant results.

Action Explanation was developed based on the results from Scoping Studies 1 & 2. It was then found to be consistently the most fixated on information type across both Information Usage studies. There are studies that corroborate with this result, but those have only used an auditory implementation. To date, no other study has indicated the importance of this kind of information.

Action Explanation *should be of high prominence on a future HMI at all times- particularly after any driving event (handover or warning) and should be displayed with the* ***Vehicle Warnings*** *icon.*

9.1.2. Auto Indicator

In the Scoping Study 1, a ‘self-drive indicator’ was requested across all driving simulation events by the majority of participants across both HIP and LIP. This type of information was not evident in the responses by attendees during Scoping Study 2, but that study did not specifically investigate the internal HMI of future vehicles. In IUS1, this information type displayed a significant increase in fixations but displayed one of the lowest overall total fixations. In IUS2, a significant decrease was observed, though the information was one of the most fixated on information types.

It is likely to be indicative of the effect of the handover events in IUS2, with participants being exposed to a greater variety of less predictable driving conditions hence increasing the use of future state information. This is an important information type, particularly after the planned handover warning, it significantly increased in fixations (51.4%) suggesting its importance for drivers to verify the vehicle's driving mode. Challenges such as mode confusion can be mitigated by providing drivers with a clear indication of who is in control of the system (S. H. Lee et al., 2014).

Auto Indicator was important across Scoping Study 1 and IUS1 & 2. It would appear that the information is important for drivers to confirm the current state of the vehicle, potentially to avoid mode confusion.

Auto Indicator *should be of moderate prominence on a future HMI during steady state driving but may be adapted to a lower prominence after an emergency handover*.

9.1.3. Battery and Energy Usage

Scoping Study 2 found an emergent theme around attendees wanting to understand energy usage information. Both IUS1 & 2 found identical usage patterns for both Battery and Energy Usage. Notably, during all driving events, the Battery and Energy Usage were paired together, and usage either remained consistent or increased in tandem. Usage always increased after any handover warning, suggesting that this pair of information should be made more prominent whenever a warning is displayed.

Battery and Energy Usage information can mitigate the effects of range anxiety (S. A. Birrell & Fowkes, 2014; Jung et al., 2015) by reassuring drivers they can complete their journey. After the planned handover warning, Battery and Energy Usage exhibited a significant increase in fixations, indicating that participants may have been concerned about the range of the vehicle. In comparison, after both handovers and the temperature warning, the information remained consistent in usage. Usage may only have increased after the planned handover warning, because participants had more time to be concerned about the range remaining, whereas the other scenarios required driver immediate intervention (or were innocuous, i.e. the temperature warning), suggesting drivers were more concerned about the primary control of the vehicle, rather than secondary information; but this would require further investigation.

Battery and **Energy Usage** were found to be important for users from Scoping Study 2. Furthermore, both IUS1 & 2 found identical usage patterns for both information types, with both being consistently fixated on during steady state driving. After any warning event, both icons increased significantly in usage and consistent after both handovers. This indicates the information is important for the use of a partially automated, electric vehicle.

Both ***Battery*** *and* ***Energy Usage*** *should be of moderate prominence on the display during steady state driving and should increase in prominence after a planned handover warning event.*

9.1.4. Hazard Scanner

The Hazard Scanner was evident in participant responses in Scoping Study 1 with ‘Communication of the vehicle’s situational awareness’ being one of the most prevalent themes. In both IUS1 and 2, the Hazard Scanner was one of the most fixated on information types. In IUS1 however, the fixations showed a significant decrease by the end of the trial week, whereas in IUS2, the fixations remained consistent. Again, this trend can be attributed to the addition of the handover task, which encouraged participants to use more future state, System Transparency information.

The significant drop in fixations to the information during purely steady-state driving (IUS1) caused challenging implications for future HMI design. Namely, the information enables drivers to be aware of future state events and act proactively in an emergency, as required at Level 2 partial automation. However, IUS1 found that during continuous steady-state driving, the drivers’ use of the Hazard Scanner dropped; a behaviour that has been attributed to the recent crashes and misuse of partially automated systems (such as Tesla’s Autopilot) (Banks, Plant, et al., 2018). Hence, it is important to consider ways in which the driver can be encouraged to use the information. While this is out of the doctorate’s scope, it raises important future research questions around the design of crucial information for partially automated vehicles.

The results after the handover and warning events also indicate that this information is only relevant to vehicles operating in automated driving mode. After both handover events, the fixations to Hazard Scanner fell significantly but remained consistent for the two warning events. Manual driving does not necessarily require information around the future state and hazards because the driver takes over responsibility. This verified the validity of the results in that the participant information usage is analogous to what would be expected in a real-world scenario.

Overall, the Hazard Scanner exhibited high usage, even when the fixations significantly fell in IUS1. The implication is that the information should be of a high prominence on a future vehicle HMI during partially automated driving, with special consideration given to its design during long periods of steady-state driving. After handover to manual driving, this information can be reduced in prominence.

Hazard Scanner was found to be important across Scoping Study 1 and both IUS1 & 2. The information type received high overall fixations across both studies and was a key emergent theme in the Scoping Study 1. After the two handover events, fixations to this information dropped significantly, though remained consistent in usage after warning events. The significant drop in fixations in IUS1 suggests careful consideration should be given to the design of the Hazard Scanner after extended periods of steady state driving.

Hazard Scanner *should be of high prominence during steady state and only adapted when the vehicle must handover control to the driver.*

9.1.5. Navigation

Navigation is an information type that most participants in this doctorate would have been familiar with, given its prevalence in automotive HMI today. In Scoping Study 1, participants requested information that would support 'knowing what the car will do'. In IUS1, fixations to the information decreased significantly and fixations were low overall. It was indicative of participants quickly building their familiarity with the route (as intended by the scenario design) and not requiring navigation information for steady-state routes. In contrast, IUS2 found that fixations remained consistent with high overall fixations, namely because routes were more varied and unpredictable for participants. After all handover events, fixations to Navigation fell significantly. Again, with the responsibility for the vehicle's control being passed back to the driver, it is understandable that Navigation was used less. Furthermore, the manual driving portion of the study only required participants to drive in a straight line, limiting the utility of Navigation. The information appears to be important during automated driving through routes the driver may be unfamiliar with and can be adapted to a lower prominence after handover and if the route is familiar to the driver.

Navigation was requested by participants in Scoping Study 1 and was seldom used by drivers in IUS1. In comparison, participants in IUS2 used the information frequently and consistently. The key difference was that, by design, IUS1 used routes that were consistent and became familiar. IUS2 used varied routes and was less predictable. Further, after both handover events usage of Navigation fell significantly.

Navigation *should be of high prominence during steady state driving around unfamiliar routes but should be reduced in prominence after handover or when navigating familiar routes.*

9.1.6. Road Signs

There were numerous themes from Scoping Study 1 that support the Road Signs information type: "…environment ahead information", "Knowing what the car will do", "Ensure the car is driving correctly", "Feeling of safety, real-time feedback". In IUS1, Road Signs showed low overall usage and no change in fixations. In IUS2, Road Signs showed high overall usage but a significant decrease. Again, IUS1's consistent road layout and steady-state driving likely contributed to the low overall usage of this future state, System Transparency information. In IUS2, it appeared that participants were initially relying on this information to confirm the vehicle's intention. A previously observed technique to draw visual attention to a particular location is to reference a familiar object (Black, 2017); in this case, the information presented road signs a driver would be familiar with. Notably, after the emergency handover usage of Road Signs fell significantly, but not after the planned handover, with Road Signs remaining the only System Transparency information that remained consistent in usage. The information still appeared to provide drivers with useful information in manual control. One use case could be that the Road Signs would highlight speed limit signs, that the driver may have otherwise missed. However, after an emergency handover, Road Signs fell significantly in usage. The unexcepted nature of the handover event may have caused participants to use this less and to only focus on the safe, primary control of the vehicle.

Road Signs appears to be important during the driver's initial experience with the partially automated system, with the information being used to confirm the vehicle's Technical Competence. Information still remains important after a planned handover, but the emergency handover may have prompted participants to use the information less as they were more concerned with the safety of the vehicle.

***Road Signs** should be of moderate prominence during steady state driving but may be reduced to a lower prominence after an emergency handover*

9.1.7. Traffic Conditions

Traffic Conditions was a prevalent theme from the Scoping Study 1, with the information being requested throughout all the driving events. During both IUS1 & 2, the information was consistently one of the lowest fixated on information types but displayed no significant change. After both handover events, usage decreased significantly but remained consistent after the two warning events. The results suggest that while overall usage was low, the consistent use of it throughout both IUS1 & 2 (steady-state and handovers) and the prevalence of the information in the thematic analysis from the first scoping study, would mean the information should be of a low prominence on the display but should not be adapted. Adaption can occur after control of the vehicle has been passed back to the driver.

Traffic Conditions was the least fixated on information across both studies but was consistent in usage. It was also one of the most prevalent information types requested in Scoping Study 1.

***Traffic Conditions** should be of a consistent low prominence on the display during any partially automated driving and should be reduced in prominence after a handover event.*

9.2. Limitations

There are limitations to the HMI recommendations made. Primarily, though the results are the consequence of four rigorous studies, across a range of different methodologies, it must be acknowledged that there is still further work to be done to validate their efficacy and impact on safety in vehicles. For example, while the presentation of Action Explanation (what and why information) was highly and consistently used by participants, there are questions as to the impact of the information on the driver's level of cognitive load or distraction during driving events. Though the recommendations argue for the adaptive display of Action Explanation (hence other information will be adapted to a lower prominence, or removed), it may be the case that drivers become more distracted by the explanation of why and be less able to respond to the driving event. What this project has contributed is the first, fundamental knowledge on how information is used by drivers in vehicles, after continued exposure and after driving events.

Considering the EngD project structure (Figure 2), the questions of *what* and *when* were the primary focus of the research and this has been evidently achieved. What remains are the questions around *where* and *how*. For example, now that the importance of an Action Explanation information has been established, research can build on this to explore different modalities of information presentation, which may reduce the impact on driver distraction.

Hence, these innovative preliminary HMI guidelines (Table 28) provide the first basis that can now be taken forward by JLR to test for their impact on the driver's performance and hence how safely the system is used.

9.3. Comparisons to Existing HMIs

A small scale investigation was carried out to illustrate how recommendations from this doctorate align with existing HMIs. Four systems were evaluated against the design recommendations: Tesla's Autopilot (Figure 40), Cadillac's Super Cruise (Figure 41) and Audi's Level 2 system (Figure 42).

FIGURE 40 TESLA AUTOPILOT (LAMBERT, 2018)

FIGURE 41 CADILLAC SUPER CRUISE (AYRE, 2017)

FIGURE 42 AUDI LEVEL 2 HMI. SEPTEMBER 3RD 2019

Table 29 below summarises the information presented in each of these HMIs

TABLE 29 COMPARISON OF INFORMATION ICONS IN EXISTING PARTIALLY AUTOMATED HMIS

Information	Action Exp.	Auto Ind.	Battery	Energy	Haz. Scan.	Nav.	Road Signs	Traffic	Veh. Warn.
Tesla Autopilot	~	✓	✓	✓	✓	✓	✓	✓	~
Cadillac Super Cruise	~	✓	N/A	N/A	~	✗	✗	✗	✗
Audi Level 2	~	✓	N/A	N/A	✗	✓	~	✗	~

Most notably, the Action Explanation information was evident in HMIs, but the presentation of the information never indicated 'why'. The Auto Indicator was also evident across all three HMIs.

First considering the Tesla HMI, almost a third of the display is given to Energy Usage, which was one of the information types that had a significant drop in fixations by the end of the week. However, for the Battery, Automated Indicator and Hazard Scanner, the prominence on the display appears to be in line with the doctorate's recommendations.

The Hazard Scanner remained important during the week of trials, suggesting it should not be adapted in size. Moreover, the Battery and Automated Indicator both dropped significantly in fixations and these are of little prominence on the display. However, it is important to note that a reduction in fixations to an information type may have been a result of participants moving their gaze to other information which they felt was better at expressing the same message. For instance, a participant may choose not to look at the Automated Indicator because they can get the same information from Action Explanation and the Vehicle Warnings. In this case, the Tesla's HMI does not provide information on the vehicle's Technical Competence. The blue steering wheel icon is the only dedicated indicator of whether the vehicle is in automated driving, and the results of this project suggest this may not be of high enough prominence.

The Cadillac places the Hazard Scanner and Action Explanation in two prominent circular spaces. Both of these appear to be supported by the findings from this doctorate, as both demonstrated high fixations and no significant change in fixations in IUS2. The HMI also indicates whether automated driving is still active and whether it requires intervention. The red steering wheel icon is of relatively little prominence on the display, but this doctorate's recommendations would suggest the prominence of Action Explanation alleviates this issue, according to the fixation results.

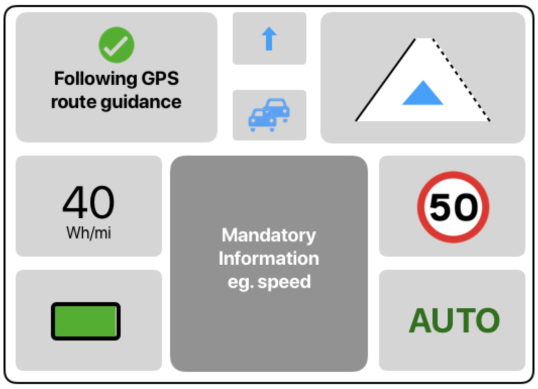
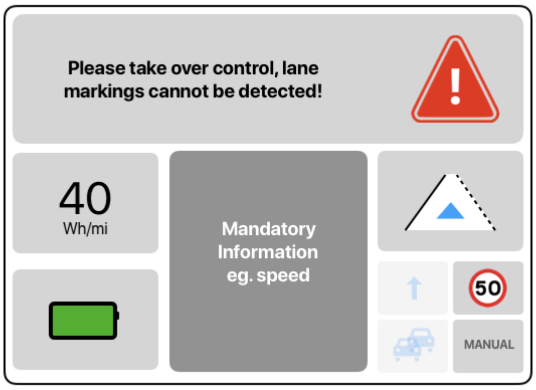
Audi's Level 2 does not provide a Hazard Scanner. Furthermore, similar to the Cadillac and Tesla, the Action Explanation. Vehicle warnings are similarly displayed on a relatively small icon, which was also the Automated Indicator. All of the HMI elements in Audi's HMI conflict with the recommendations from this doctorate.

Based on the design recommendations, the HMIs currently deployed in three of the most popular partially automated systems could be better designed to present more relevant information to the driver. Particularly, explaining why an action was taken was an important design recommendation and is missing in all cases.

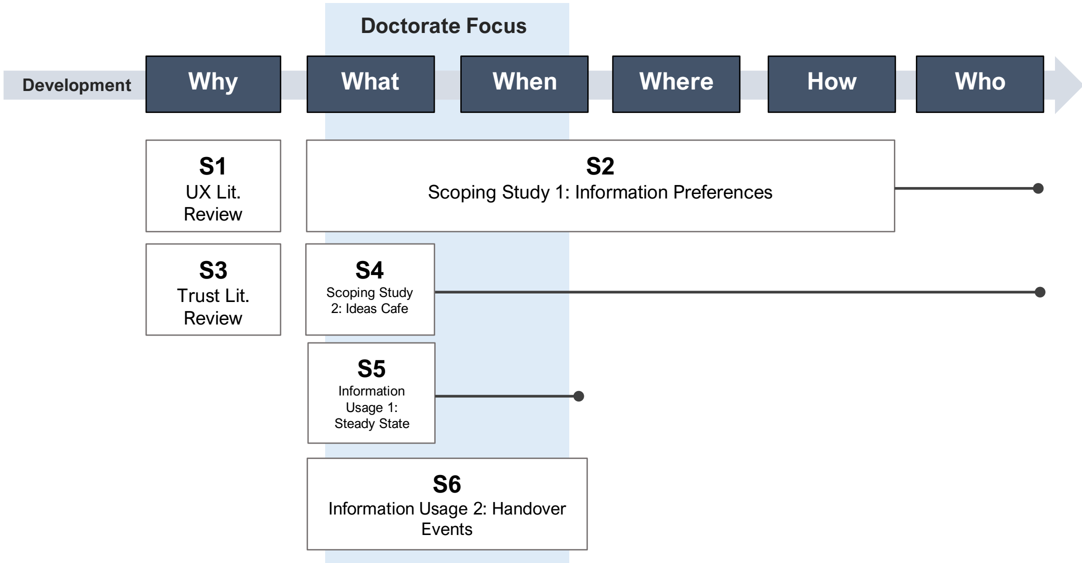
9.4. Summary

To help illustrate the results, three concepts are presented below to highlight how information adaption could be achieved. It is important to note, these are only illustrations of relative information type prominence and how this could change according to different events. Furthermore, there may be more than three versions of the HMI that could be displayed (such as after a temperature warning etc.) which are not illustrated here. These concepts have not been validated experimentally but provide a useful illustration of the topics for exploration in future research. The examples are shown below in Table 30.

TABLE 30 EXAMPLES OF HMI CONCEPTS AND HOW INFORMATION COULD BE ADAPTED

HMI	Information Adaption
	• **HMI during steady-state driving.** • Action Explanation (paired with Vehicle Warnings) and Hazard Scanner feature prominently. • Energy Usage and Battery are paired and feature with moderate prominence. • Road Signs and Auto Indicator feature with moderate prominence. • Navigation and Traffic feature with low prominence.
	• **HMI after an emergency handover.** • Action Explanation (paired with Vehicle Warnings) feature with increased prominence. • Hazard Scanner has been reduced to moderate prominence. • Road Signs and Auto Indicator have been reduced to low prominence. • Navigation and Traffic have been reduced further.
	• **HMI after planned handover** • Action Explanation (paired with Vehicle Warnings) feature with increased prominence • Hazard Scanner has been reduced to moderate prominence • Road Signs and Auto Indicator remained consistent • Navigation and Traffic have been reduced further.

These examples are initial concepts of what an adaptive HMI could look like. This doctorate aimed to define the information preferences and usage for drivers of partially automated vehicles; how these definitions are used is dependent on its application for industry in the design of future HMIs.



Considering the research structure presented above, the doctorate's focus has centred around *what* information drivers use. There are still more use cases of *when* that need to be explored in future research. This doctorate answered several specific cases such as steady-state driving in familiar and unfamiliar routes, emergency handovers, planned handovers, generic warnings and handover warnings, but there are more test cases possible. What has been achieved is a comprehensive understanding of *what* information should be presented based on four studies utilising three different methodologies. How the adaption of information should occur and where it is displayed is dependent on the design motivations of the industrial company using the data from this study. There may be branding styles, fonts and animations that, for instance, Jaguar Land Rover will need to implement which has not been considered in this doctorate. Hence the sample HMIs in Table 30 represent only a glimpse of how information could change in response to different events.

This report will now consider the impact of this research and how it should move forward in the future.

10. Research Impact

This doctorate aimed to understand how HMIs can more appropriately support the driver in the use of a partially automated vehicle system. To achieve this, this doctorate set out the following objectives:

1. To understand the prominent challenges in designing HMIs for partially automated vehicles.
2. To understand driver information preferences inside partially automated vehicles
3. To define the types of information required for future partially automated vehicle HMIs.
4. To understand how the usage of these types of information change with increased familiarity with the system and after certain driving events
5. To utilise this learning to recommend what information should be presented inside future partially automated vehicles and how this can be adapted over time and according to different driving events.

The first objective was met with the initial literature review in Submission 1: UX Literature Review, defining the key challenges from a broad perspective. Objectives two through five were all addressed through the four studies in this doctorate.

Given the key requirement of the EngD being the demonstration of the industrial impact of the work, this section will begin by addressing specifically how the work has been adopted by JLR. Following this, each of the project objectives will be discussed in relation to the impact of the research, from the perspectives of academia, the sponsoring company, Jaguar Land Rover and the wider industry.

10.1. JLR Impact

The challenge of understanding how HMIs can more appropriately support the driver in the use of a partially automated system addressed a key industrial need both for JLR and the wider industry. The research was designed from the outset to address a future area of development for JLR, with their upcoming automated vehicle systems. Hence there was a continual theme through the four major studies of this EngD of ensuring the research was answering questions that would be valuable to JLR.

The HMI recommendations developed (Table 28) from the holistic combination of the four studies, have been disseminated by the EngD candidate across multiple teams at JLR. The industrial experts at these meetings came from a wide range of backgrounds, including psychologists, HMI engineers, programmers, ergonomists and senior management. Having presented at these meetings, it was evident that the results contributed to JLR’s deliverables by providing the key, innovative HMI recommendations that can now be taken further across their research teams. In particular, senior HMI research managers have expressed their intention to use the research as the basis for new, highly focussed studies. Specifically, the results around the Action Explanation information, provide JLR an opportunity to implement what was found to be a key HMI requirement, not yet observed in competitor vehicles. Furthermore, the shortlist of information developed and disseminated across JLR, provide a rigorously derived methodological tool for their future studies. It is understood that this list will be used in JLR studies wherever a representative future HMI is presented.

On the topic of methodology, the project's studies have demonstrated the practical feasibility and innovative value of testing automated technology using immersive driving simulators across a range of different methodologies (both qualitative and quantitative). Specifically, how qualitative results can be used to define and design the requirements for a quantitative study. Moreover, it has also been expressed by JLR engineers, that the unique longitudinal assessment of HMI in IUS1&2 has given them an important insight into the value of testing over multiple exposures, which now forms a key consideration in the design of their future studies.

10.2. Scoping Study 1 [Objective 2]

Information Preferences Inside Partially Automated Vehicles

Ulahannan, A. et al. (2020) 'User expectations of partial driving automation capabilities and their effect on information design preferences in the vehicle', Applied Ergonomics, 82, p. 102969. doi: https://doi.org/10.1016/j.apergo.2019.102969.

To summarise the results from Scoping Study 1:

- In-depth exploratory approach afforded by the semi-structured interview methodology led to the development of a new method of grouping of drivers according to their information preferences: High Information- and Low Information Preference drivers (HIP/LIP).
- Demonstrated the importance of considering the driver's expectations of the technology and how this impacted the information they preferred when using the partially automated system.

The results contributed to a better understanding of who the drivers of partially automated vehicles are and how their information preferences change. Through the development of the HIP and LIP categories, the study explicitly highlighted the importance of creating HMIs that can support a wide variety of drivers and preferences. The first challenge in the majority of design processes is to understand who the users of a product are (Gultekin et al., 2016; UK, 2019). Using these categories, HMI designers are provided with a better understanding of who their users are and will be better equipped to consider how their HMIs can support the drivers.

Consequently, this has an important impact on industry. Jaguar Land Rover designers now have a detailed overview of future customer information preferences to make informed decisions on the presentation of information on a future HMI. At the beginning of this Innovation Report, the consequences of HMIs failing to support the driver appropriately were detailed (mode confusion, distraction and the potential for accidents). The recognition of different types of information preferences can be implemented into the HMI design process early, to ensure drivers who tend to use information less or have inappropriately higher expectations of the capabilities of a partially automated vehicle, can be tested and designed for. It provides industrial researchers who test future HMIs with users, the key research questions and the metrics to measure and be aware of, for example, to specifically ensure LIP drivers appropriately use the HMI design being tested.

Outside of the automotive context, in the wider industry, there is a recognition that there should be a clear understanding of who the users of a product/service are and how they perceive their use of the product. This is evident in the aforementioned design process models from the British Design Council and Gultekin et al. (2016), but also in the use of similar techniques such as user personas (Miaskiewicz & Kozar, 2011). The specific results around HIP and LIP drivers are likely to only apply to the unique conditions a partially automated vehicle creates. It asks drivers, who may have received their driving licence anywhere between the ages of 18-70 years old, to use a system that requires no formal training, in traffic with other road users who may be unaware that it is a partially automated system in control.

It is difficult to imagine a comparable situation in the wider industry. For example, in contrast, pilots receive regular training and are required to be tested on new features introduced into aircraft. Furthermore, training is specific to a particular manufacturer (Airbus or Boeing) and requires retraining to move between the two. In the context of autonomy in manufacturing, operators will be provided specific training on how to use the machinery and its exact capabilities. This is not the case in the automotive sector, with drivers being able to use partially automated systems without any training or education on its capabilities. Hence, the HIP and LIP are specific to the partially automated vehicle context and are an important contribution for future HMI designers.

The methodology applied here applies to many different contexts where user preferences are important. The semi-structured interview format allowed for a holistic, broad inquiry into user requirements and has been used before to understand user requirements (Trösterer et al., 2017). Furthermore, the study also found that the 3xD's BUC was too high in fidelity for participants to feel like they could suggest design changes, an effect that was observed in the field of product prototyping (Hall, 2001; Rudd et al., 1996). This is an important consideration for industrial designers working on any user-facing system; lower fidelity prototypes should be used in studies where the aim is to understand how users would prefer a product to be designed.

The results in this study contributed significantly both to the final design recommendations for the information that should be presented inside a partially automated vehicle and methodologically for how this kind of research can be undertaken in the future.

10.3. Scoping Study 2 [Objective 2]

Information Preferences Inside Partially Automated Vehicles

Ulahannan, A., Cain, R., Dhadyalla, G., Jennings, P., Birrell, S., Waters, M. and Mouzakitis, A., 2018 Using the Ideas Café to Explore Trust in Autonomous Vehicles. In International Conference on Applied Human Factors and Ergonomics (pp. 3-14). Springer, Cham.

Ulahannan, A., Cain, R., Dhadyalla, G., Jennings, P., Birrell, S., Waters, M. 2018 The Ideas Café: engaging the public in design research. In Proceedings of DRS 2018: Catalyst Vol. 1 (p.1175-1193).

To summarise Scoping Study 2:

- A broad set of results, spanning across society and policy, data and privacy, inclusive design principles and the internal HMI.
- The methodology was successful in bringing together a range of demographics in conversation and confirmed the importance of defining the information presented inside an automated vehicle.

The work provided two key contributions. First was the recognition of several key future research questions, specifically, a number of the themes identified contributed directly to the information design recommendations. Second, the methodologies deployed in the event provided a unique method of involving users in conversation and has typically not been formally used in automotive engineering contexts before. Namely, the spectrum lines, table conversations and the setting of the Coventry Transport Museum were successful in bringing together a broad range of demographics into a cohesive conversation around the topic of trust in automated vehicles. The methods used provide a template for future public engagement events, both for academia and industry.

This is also true outside of the automotive context. The development of the Ideas Café agenda deployed on the day was largely based on literature regarding public engagement events that have been used frequently to gather public opinions on issues with multiple stakeholders (Ebdon & Franklin, 2006; Kweit & Kweit, 1981; Yang & Pandey, 2011). Consequently, across the wider industry, the methods remain consistent.

10.4. Information Usage Studies 1 and 2 [Objectives 3, 4 & 5]

Definition of Representative Information types and How Their Usage Changed

Ulahannan, A. et al. (2020) 'Designing an Adaptive Interface: Using Eye Tracking to Classify How Information Usage Changes Over Time in Partially Automated Vehicles', IEEE Access, 8, pp. 16865–16875. doi: 10.1109/ACCESS.2020.2966928.

Ulahannan, A., Birrell, S., Jennings, P and Thompson, S. 2019 Designing an Adaptive Interface: How Information Usage changes following Handover and Warning Evens in a Partially Automated Vehicle. In IEEE Access **[Under Review]**

Ulahannan, A., Birrell, S., Thomson, S., Skyrpchuk, L., Mouzakitis, A., 2019. The interface challenge for semi-automated vehicles: how driver behaviour and trust influence information requirements over time. Intelligent Vehicles Symposium 96–101.

Ulahannan, A., Birrell, S., Thomson, S., Skyrpchuk, L., Mouzakitis, A., 2019. The interface challenge for partially automated vehicles: how driver characteristics affect information usage over time. Book on Human Factors in Intelligent Vehicles **[Accepted]**

To summarise the two Information Usage studies:

- Information usage does change with increasing familiarity with a partially automated system
- Information usage does change after driving events (handovers and warnings)
- Highlighted the importance of 'Action Explanation' an information type that described what the vehicle was doing, and why
- Developed a list of information recommendations for future partially automated vehicles, based on a synthesis of all studies in this doctorate.

Both IUS1 and 2 represent the most significant quantitative results in this doctorate. To date, they were the first studies that aimed to classify information usage inside partially automated vehicles longitudinally over time. Moreover, to date, the continuous steady-state scenario deployed in IUS1 is also unique. There are three key impacts of these studies.

First is the impact on future HMI design. The unique longitudinal study design allowed for information usage to be recorded over time. The changes observed for information usage during steady-state driving confirm the results that approached the problem from a cognitive workload perspective (Banks, Eriksson, et al., 2018; Banks & Stanton, 2019); drivers shift away from using important future state System Transparency information, in favour of information that confirms the Technical Competence of the vehicle. This can limit how capable they are of taking back control of the vehicle in a critical situation. Academically, this is an important result that highlights the need for more design research on how this kind of information could be presented to ensure it is appropriately used by drivers; and this study has specifically highlighted what information needs to be considered for future research.

The other big contribution was the importance of Action Explanation, an information type designed out of Scoping Studies 1 & 2, that was consistently the most used information across both IUS1 and 2. Furthermore, it was not present in any existing HMI, indicating a significant opportunity to design and implement a type of information that this doctorate has found to be of significant importance to users. This is of interest to future work and requires further exploration around the wording and the kinds of language that could invoke the most appropriate driver response.

Secondly, from a methodological perspective, IUS1 & 2 have contributed to a better understanding of how HMIs can be tested over a period of time. At the time of the study, there had not been another study that had aimed to study information requirements, and it was unclear how long these studies should be run for. The studies have both demonstrated how a five or three-day longitudinal study could work and most importantly, the benefit of testing over this period of time as the usage of the HMI was found to change significantly over time.

The design guidelines on what information should be shown in a partially automated vehicle are the first of its kind. This has important implications for academic research but also for industry. An HMI that is appropriately designed has consequences not only for the user experience for customers, but also for the safety of the vehicle. Estimates from Accenture suggest that the increasing prevalence of automated vehicles is a large opportunity to expand insurance offerings (Accenture, 2019) as a result of the increased vehicle safety. A vehicle whose HMI better supports the driver and can keep them in the loop and attentive is likely to attract lower insurance premiums for the use of its partially automated system. This could be an important differentiating factor when marketing a partially automated system.

10.5. Reflections on the Doctorate

This section reflects on the overall doctorate process and how the doctorate could be done differently to address the same aims and objectives.

The use of a driving simulator was one of the key aspects of this doctorate with three out of the four studies using the facility. Section 3.1 goes into detail regarding the limitations and benefits of using driving simulators. They enabled the testing of driving scenarios that would otherwise have been prohibitively expensive or in some cases unsafe to test. While absolute values from simulator studies are less generalisable, the relative differences are still valid. The design recommendations should now be taken forward into real-world trials. This should be done in two ways, first by repeating the same eye-tracking study but in a real-world condition. With the specific research objectives defined, the new trials can specifically test the theories developed from the simulator studies in this doctorate. Second, following this real-world trial, the impact of an adaptive HMI on various different driver metrics, such as: handover performance, user experience, trust, workload and situational awareness should be assessed. This would involve prototyping an HMI (that may be similar to those presented in Table 30) and deploy this inside a partially automated test vehicle with participants in a controlled environment, such as a test track.

With regards to the use of driving simulators, this was the most appropriate choice for the conditions being tested, and the fact that little was known about the area of information requirements and many factors (such as experimental design) were being defined for the first time without previous studies to build on.

The other significant decision made in this doctorate was around the length of the longitudinal trial. IUS1 used a five-day design, and IUS2 used a three-day design. Future research could move to use the three-day design immediately. The shorter design presented the same number of scenarios as the longer IUS1 but brought about significant benefits regarding participant scheduling. The inflexibility of scheduling in IUS1 meant the loss of three participants' data, IUS2 was much more flexible, accommodating participants better and more efficiently. The significant trends observed is a strong indication that studies using a single exposure are not representative of real-world HMI usage and this is a significant methodological contribution of this doctorate.

The final aspect was the use of eye-tracking. This was found to be heavily time-consuming, requiring manual mapping of eye-tracking data points to a reference image. The time intensive process took approximately 2-3x the real-time speed of the simulations recorded. Across multiple participants, this was a significant amount of time spent on analysis. While automatic mapping was available, the unreliability of the software meant it was not used. However, in the weeks following the study, new APIs that could connect to the Tobii software were found, which could significantly reduce the data analysis time. Future research should consider these options before undertaking eye-tracking research to optimise the time spent on manual coding of eye-tracking data.

10.5.1. Wider Impact and the Future Work Required

This doctorate focussed on Level 2 partially automated vehicles, but as the levels defined by the SAE indicate, there are higher capabilities of automated driving yet to come. As technology progresses, there will be different challenges for drivers and the HMI. The key difference being around where the responsibility for the control of the vehicle lies. Currently, with partially automated vehicles, this lies with the driver at all times, but this changes at higher SAE levels. The results in this study still hold value for these higher capabilities, though presumably there will be less of a requirement for drivers to act proactively on the information, Scoping Study 2: Ideas Café would suggest that this information is still important for trust and acceptance, even at higher levels of autonomy.

Furthermore, the steady-state scenarios presented in IUS1 emulated the experience of a vehicle with a higher level of automated capability; being able to handle all of the driving conditions presented and not requiring a handover of control. With the results finding no significant decrease in the usage of certain information types, again, there is a strong suggestion that these recommendations remain true for higher levels of autonomy.

Future work in the automotive space should use the information design recommendations made in this doctorate to continue to develop prototype HMIs that are better able to support drivers; at the partially automated level and beyond. By developing these information recommendations, researchers can be better equipped to test future HMIs and focus research questions on how information should be presented, which modalities should be used and the practicalities of an adaptive HMI.

When considering the application of the results to the wider industry, there is value in the methodology used to develop the recommendations. This doctorate has shown how three very different methodological approaches can be combined to create holistically derived design recommendations. This approach to solving a design challenge can be applied universally. Using a qualitative approach to define the problem and begin to scope out solutions, then following this up with a detailed quantitative, longitudinal approach has been successful for this doctorate. Any challenge that involves human users can benefit from this as it allows exploring a breadth of options at the beginning, then focussing on a specific challenge that is evident from the initial scoping. Furthermore, from a wider perspective, the results and recommendations are concerned with the interaction between a human and an automated system. Hence, it is possible the results around the presentation of an explanation of ‘what’ and ‘why’, pairing detailed information with iconic representations and a consideration for how the usage of these types of information change over time with increasing familiarity with the system, apply across a range of different human-automated interaction contexts (outside of automotive design). For example, consumer electronics are increasingly moving towards an Internet of Things model, where systems can talk to each other to automate a wide array of common functions, such as email, home appliances, news aggregation (Lohan & Singh, 2019). In all these contexts, users are required to learn how to interact with a system that is increasingly taking over tasks that the user would have typically managed themselves. As a result, human factors challenges are becoming more evident and there are opportunities to improve the user experience associated with this move to increasing automation (Karthick G. S. & Pankajavalli P. B., 2018). The results from this project, could provide the early research directions in understanding how a wide variety of automated system interfaces can be designed to better support the user in their information needs. For example, if a user encounters unexpected behaviour or an error while using a computer or smartphone, could an Action Explanation information be also provided to give a reason as to what has gone wrong, and why?

Given that automation is becoming more prevalent in more aspects of our lives, both the methodologies used and the recommendations developed in this project, could provide the early contributions to a wide range of future interface design research and industrial applications.

11. Conclusion

This doctorate aimed to understand how HMIs can more appropriately support the driver in the use of a partially automated vehicle system. This aim was addressed by proposing design recommendations for the information that should be presented inside a partially automated vehicle; and how this could adapt over time and after specific driving events.

This doctorate found:

- Driver expectations of the capability of an automated system affect their information preferences. Two groups were defined (HIP and LIP drivers), which highlights the importance of designing an HMI that accommodates different user perceptions.
- Based on the results from two Scoping Studies and collaborative workshops with industry, a shortlist of information that should be presented inside a partially automated vehicle was developed and presented. This shortlist is valuable for future partially automated HMI research.
- During steady-state driving, along routes the driver was familiar with, important future state information was used less. Drivers wanted only a confirmation of the vehicle's technical competence. However, by understanding and characterising the change in information usage, HMI designers can now take advantage of these findings to ensure this kind of information can be designed appropriately.
- Across both Information Usage studies, the Action Explanation information type was consistently the most used information by participants. Notably, this information is not present in the form tested in this doctorate in any HMI currently available.
- Longitudinal testing of HMI is important to ensure a more robust understanding of its use. The Information Usage studies found significant changes when participants were exposed to an HMI over multiple exposures, suggesting that the single exposure studies to date are not an accurate reflection of the real-world use of an HMI.

For the sponsoring company Jaguar Land Rover, this doctorate has provided them with a robust set of design recommendations for the information presentation in partially automated vehicles. HMIs that can be designed that can more appropriately support the driver in a partially automated vehicle; creating a superior user experience in their vehicles. The results also apply to the design of HMI in vehicles with higher levels of driving automation (Level 3-5).

This doctorate has provided a comprehensive look at information requirements for partially automated vehicles. The results and recommendations derived are the first of their kind, but the contributions also extend to the innovative methodological approach that was taken. Successfully synthesising the results of three different methodological approaches has resulted in a robust and holistically derived set of design recommendations. These design recommendations can now be taken forward to design and test new HMIs that can create a better, safer experience for future automated vehicles.

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