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User expectations of partial driving automation capabilities and their effect on information design preferences in the vehicle

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ABSTRACT

Partially automated vehicles present interface 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 grounded theory. From the results, two groupings of driver expectations were identified: High Information Preference (HIP) and Low Information Preference (LIP) drivers; 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.

1. Introduction

The automotive industry has begun the transition to driverless car technology (Muller, 2016). Currently, driving automation known as SAE Level 2, or Partial Automation (SAE, 2018), such as Tesla's 'Autopilot' (Endsley, 2017), Mercedes' Distronic Plus system (Singh et al., 2019) are emerging on the market. According to the SAE definitions, the responsibility for the vehicle's driving performance on the road at Level 2 still remains with the driver (Banks and Stanton, 2016). Through constant monitoring of the driving automation, the driver must be able to recognise the operational design domain (ODD) of the system and intervene appropriately (SAE, 2018).

However, it is well recognised in many previous studies that typically humans can have difficulty with being a monitor of an automated process (Brookhuis et al., 2001; Dzindolet et al., 2003; Kaber and Endsley, 2004; Sheridan, 1995). This has been attributed to the denser cognitive demand when the user is asked to monitor an automated process as opposed to driving it themselves (Rafferty and Stanton, 2017; Walker et al., 2010).

Ensuring humans are able to safely use Level 2 partially automated driving systems is important because these systems will increasingly be responsible for the safety of the vehicle's occupants and other road users. Without careful design consideration, they can present many challenges for the driver, for example: mode confusion, where the driver is unsure of the parts of the driving task that are within the system's ODD (Banks et al., 2018; Martens and van den Beukel, 2013); over- and under-reliance on the system caused by an inappropriate level of trust (Khastgir et al., 2018; Hoff and Bashir, 2015); increased cognitive workload (Stapel et al., 2019) and consequently usability (Ulahannan et al., 2018).

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An appropriately designed human machine interface (HMI) has been recognised as a method to mitigate these problems, by supporting and communicating with the driver to understand the system's ODD (Choi and Ji, 2015; Schaefer et al., 2016). For example, the most prevalent Level 2 system available today is the Tesla Autopilot and its approach to HMI design has been to present the driver with a variety of different information about the driving automation (Olsen, 2018). This is, however, an example of inappropriate communication as this approach to driver communication has been shown to be ineffective, causing either cognitive over- or under-load, over trust and consequently increase the risk for accidents (Banks et al., 2018; Lyu et al., 2017; Manawadu et al., 2018). This is illustrated aptly by the incident of a Tesla driver who after activating Autopilot, moved into the passenger seat-far exceeding the ODD of the system. The challenge for the HMI is to educate drivers on this new system and paradigm for driving (Kyriakidis et al., 2019).

To better understand how drivers can be supported through the vehicle's HMI, driving simulators are often used-providing a safe and repeatable environment. How driver experience and trust effect the use of Level 2 automated driving have been investigated using driving simulators (Beller et al., 2013; Hergeth et al., 2016; Lyu et al., 2017). More exploratory qualitative methods have been used to assess the specific information preferences of such HMI (Beggiato et al., 2015; Richardson et al., 2018). These studies have used a combination of interviews, expert focus groups and ethnographic methods. Beggiato et al. (2015) used a static driving simulator with a 180° field of view, which may have limited the immersion of the scenarios and hence the results. There was an opportunity to apply these qualitative methods to investigate and validate these information preferences in a more immersive driving simulator.

1.1. Methodological approaches to investigating information preferences

Qualitative methods enable a broader, more exploratory inquiry into challenges around user experience and preferences than can typically be achieved through quantitative methods (such as questionnaires) (Choy, 2014; Parker et al., 2007; Yauch and Steudel, 2016). Semi-structured interviews can give a richness of data to enable the exploration of driver expectations and preferences. This is achieved through the coding of participant responses and subsequently developing themes and noting trends in language style and the vocabulary used (Louise Barriball and While, 1994). This depth of data is typically difficult to obtain through Likert scales or more structured interview formats. Then by refining the qualitative data against theoretical frameworks, there can be greater structure and validity given to the data (Dubois and Gadde, 2002; Patton, 2014). Combining qualitative methods with a high fidelity driving simulator can enable the exploration of information preferences and expectations of partially automated vehicles. Furthermore, designing for automotive usability is an inherently holistic challenge (Meschtscherjakov et al., 2011; Steinberger et al., 2015) and consequently a high fidelity simulated environment provides opportunities to capture a richer range of data.

Models such as Michon's Levels of Driving (Michon, 1985) or Rasmussen's Skills, Rules, Knowledge (Rasmussen, 1983) (SRK), all recognise that information can be interpreted and acted upon in different ways by different users (Kirwan, 2017; Vicente and Rasmussen, 1988). Considering the SRK model by Rasmussen (1983), this categorises human action into intuitive behaviour that requires little cognitive exertion (Skills), to more cognitively demanding action (Knowledge). Taking the example of a learner driver, it is likely the action of changing gears will require a lot of cognitive effort (hence knowledge behaviour), whereas an experienced driver will find the same process intuitive, requiring little to no cognitive effort (Skills) (Harwood and Sanderson, 1986). This also applies to the interpretation of new vehicle information, for example, energy usage inside an electric vehicle. Often this is presented to the user as a combination of Watt-hours used per mile (Wh/mi with the Tesla Model 3 or miles/kWh in the Nissan Leaf). Research by Birrell et al. (2014) showed that a common theme from the subjective comments of novice EV users was the unpredictable nature of the range estimations, with little understanding as to what is the actual root cause of the inaccuracies, resulting in increased anxiety about how far their vehicle could travel (Birrell et al., 2014). This is an example of how information is presented can effect the user's experience of the system.

Consequently, it is of interest to this study to understand the information preferences for drivers of a partially automated vehicle and hence how these are affected by their expectations of the technology. In comparison to manual driving, it has been found that drivers using Level 2 automated driving systems are more likely to engage in a secondary task that can draw their attention away from the road (Lin et al., 2018; Llaneras et al., 2017). Further, large differences in drivers' expectations for the development of automated driving systems have been found (Kyriakidis et al., 2015) with some drivers expected SAE Level 3 conditional automation as early as last year (2018) and SAE Level 4 by 2025, which can cause issues with over-reliance and misplaced expectations (Underwood, 2014).

Using this information, there can be more informed design choices made to ensure partially automated vehicle interfaces can be used effectively by a wide array of drivers. Therefore there is an opportunity to investigate these varying driver expectations of partially automated driving and their subsequent effects on information preferences in the vehicle.

1.2. Aim

This study aimed to investigate the drivers' information preferences for Level 2, partial automation, and how their expectations of the system's capability affected their information preferences, using semi-structured interviews in an immersive driving simulator.

2. Materials and methods

In order to investigate information preferences, an 8 min driving scenario was developed and presented to participants in the driving simulator at WMG, University of Warwick. Within this scenario, 5 driving events occurred. The WMG 3xD Simulator for Intelligent Vehicles (thereinafter 3xD) featured a Range Rover Evoque Built Up Cab (thereinafter BUC) (Figs. 1 and 2). The BUC was positioned in the centre of a 360° projected screen. The scenario presented in the 3xD was controlled from an external control room adjacent the simulator. Further, all existing vehicle interfaces were turned off to prevent participants from being influenced by what was already present inside the vehicle.

After each event, semi-structured interviews were conducted. The semi-structured approach was chosen as it allowed for a more effective exploration of the information preferences. This 360° simulated environment around the BUC allowed the participants to notice things outside of the primary driving task, such as what was happening at the vehicle's rear, or at the sides.

Ethical approval for this study was granted by the University of Warwick's Biomedical and Scientific Research Ethics Committee for the study REGO-2016-1788.

2.1. Participants

All 25 participants completed the user trial. 8 participants mentioned feeling nauseous during the first event but recovered and were happy to proceed with the study. No participants withdrew from the study. A breakdown of the participant demographics can be found below in Table 1.

2.2. Driving scenario

A section of LiDAR scanned, photorealistic simulation incorporating

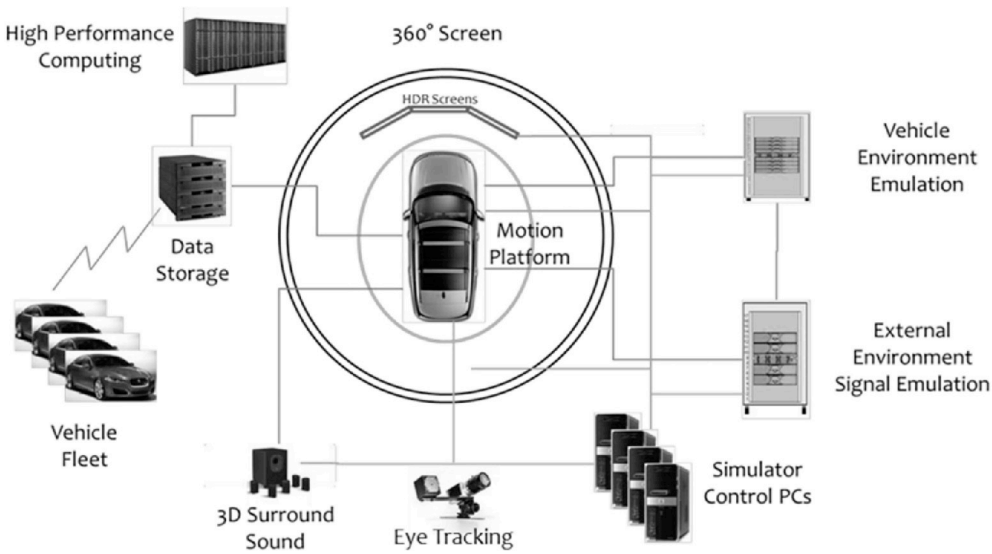

Fig. 1. Schematic for the WMG 3xD Driving Simulator (note, not all the equipment detailed in the diagram was used for this study).

Fig. 2. 3xD with LiDAR scanned imagery displayed.

Table 1
Participant demographic information.

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)

a real-world residential arterial road in a city (A4114, Coventry, UK) was used to increase the immersion of participants in the driving scenario. It provided 1.5 miles of a single lane urban environment through a residential area. One uninterrupted run of the scenario took 8 min to complete.

The simulator software (provided by XPI Simulation Ltd) was then used to add pedestrians and other road vehicles onto the map to increase the authenticity of the replication. All vehicles in the scenario were manually scripted to follow a predetermined path. The scenario featured five events, detailed in Table 2, these were not emergency events, but designed to reflect real-world situations that Level 2 vehicle could be expected to handle.

Table 2
Event descriptions and corresponding interview prompts.

Event	Description
1	Vehicle offers automated driving to driver and is activated.
2	Vehicle autonomously navigates heavy traffic
3	Vehicle navigates through a junction
4	Vehicle follows another vehicle in steady state
5	Vehicle requests and hands back control to the driver

2.3. Topic guide

The study used a semi-structured interview format. To explore information preferences for partial driving automation, the following topic guide was developed 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?

A set of probes were planned to aid the participant in elaborating on their response and to help build rapport, following guidance by Leech (2002) and Turner III (2010). The following phrases were used *"Would you elaborate on that point?"*, *"Could you give an example of that?"*, this was important as the 3xD Simulator environment was likely unfamiliar and novel to most participants and the interview probes would help participants struggling to engage in the interview (Leech, 2002; Turner III, 2010).

2.4. Experimental procedure

The experimental procedure was as follows:

(1) Participants were invited into the WMG 3xD Simulator room and reviewed the procedure with the investigator. Written consent was taken from the participant at this point, however they were free to withdraw at any point. All participants were volunteers and did not receive payment for participation.
(2) Participants were invited to sit inside the BUC in the WMG 3xD Simulator and were briefed on the potential side effects of motion sickness. They were then given a lay summary of the vehicle's partially automated capabilities, including its limitations and were instructed to monitor the driving task as they would be required in a real partially automated vehicle.
(3) After each of the five events in the simulation (detailed in Table 2), the playback was paused and the participants were interviewed using the interview schedule. The total time for the scenario playback was 8 min, with each event being approximately 1 min long. In total, participants spent approximately 30–40 min in the simulator, depending on how long responses were.
(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.

2.5. Participant sampling

Limited simulator availability (10 days) required quick recruitment and access to participants. Therefore convenience sampling was used, meaning participants were located at or close to the University of Warwick. The study was advertised through a network of colleagues and in social areas at WMG and across the University of Warwick campus, with a total of 25 participants being recruited (Gender: 16M/9F, all students/staff at the University of Warwick).

2.6. Data analysis

There were two key parts to the data analysis:

(1) To understand information preferences in partially automated vehicles (based on the topic guide in section 2.3), 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.

2.6.1. Overall information preferences

A coding strategy was used for all data: structural, descriptive, process and in-vivo coding (Saldaña, 2009). Structural coding was used to organise the interview responses by the question answered (Namey et al., 2008). The remaining strategies all enabled the discovery of driver expectations and their corresponding effect on the information preferences. Descriptive coding summarised responses into words or phrases. Process coding analysed responses by observable and conceptual actions, such as gestures or areas the participant pointed to (Corbin and Strauss, 2014). These actions were noted by the researcher as field notes during the interviews and supplemented after the experiment using the video recorded footage from inside the BUC. Finally, in-vivo coding recorded the exact phrase used by the participant.

This process was completed independently by two qualitative researchers who then compared results, creating a collaboratively derived list of codes. By categorising the type of coding used, it enabled the application of a consistent methodology in the coding of the interview data. For each type of coding, multiple cycles were ran until a theoretical saturation point was reached (to reduce the risk of subjectivity in analysis) (Bowen, 2008).

The second phase of coding explored common themes between the codes and synthesised them into categories, providing a conceptual model for the user preferences for Level 2 driving automation. This process was repeated, creating a more refined list of categories (Corbin and Strauss, 2014). An example of this process is shown below in Table 3.

The number of times a code was mentioned by participants was also tracked. It can be noted that frequencies are often greater than the number of participants. This is because each participant may have mentioned the code more than once in their response.

2.6.2. Driver expectations and their effect on information preferences

The codes were then reviewed holistically to understand if there were groupings in how participants responded beyond the structural coding of the topic guide in the first part of the analysis. Differences in driver expectations could be identified and hence compared with their information preferences for each of the driving events.

To illustrate any differences in the information preferences, the data was categorised according to Geiser's Model (Geiser, 1985). This describes how information in the vehicle can be organised into Primary information (information related to the directional control of the vehicle, e.g. handover notifications), Secondary information (information that supplements the control of the vehicle, enabling its safe use, e.g. hazard scanner) and Tertiary information (information that enhances the driver's experience, e.g. intelligent suggestions such as petrol

Table 3
Example from the coding process: from transcript to final theme.

Transcript	Example Descriptive Codes	Theme
"Car should give me some information about the traffic ahead, if I'm not going to drive then I need some information about what's around. Then I want some kind of indication that automated driving is activated, like some light maybe and how long it can self-drive for?"	How long automated driving can last Self Driving Indicator Light Information about Traffic Ahead Information about the Environment	Communication of the state of handover Communication of the vehicle's awareness of its surroundings

stations, nearby friends).

3. Results

From the interview transcripts, a total of 719 first cycle codes were generated, these were thematically grouped according to the interview topic guide, then by the driving event.

Table 4 below shows an overview of all of the themes and the codes that comprised them. In addition, the frequency of each code is indicated in brackets next to the code as (f = …). The table also indicates for which event the code was in relation to. It was found that some were unique to the driving event, whereas others were mentioned across all driving events.

3.1. Overall information preferences

The most popular theme, summarised in Table 4, was concerned with the communication of the vehicle's situation awareness (f = 174). Within this, information about traffic conditions and information about the road ahead was requested across all the driving events (f = 74). Communication of the state of handover was the second most mentioned code (f = 95).

The next three major themes were all concerned with the overall presentation of information. Participants were split, requesting either that the information was displayed all the time (f = 37) or more intelligently in response to road conditions (f = 59). Participants then requested that information should be located in existing interfaces (f = 140). There was a consistent theme of the information being easy

Table 4
Overview of the codes comprising the themes and corresponding frequencies.

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 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 takeover (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 interfaces (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)		–	–

and familiar to access (f = 22) across all the events. Those participants who suggested specific locations (such as the centre console or dashboard), suggested them consistently across all the events. Similar to the theme of information being familiar and easy to understand, the theme of information requiring minimal learning was present across all participants (f = 117).

The final theme suggested that participants only expected limited interactions with the vehicle during driving automation (f = 65). Though 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).

In the following section 4, the codes within each of the themes will be discussed in more detail with respect to the literature.

3.2. Driver expectations and their effect on information preferences

Two groupings of participants were evident in the codes: those with High Information Preferences (HIP) and those with Low Information Preferences (LIP). Overall, HIP participants wanted detailed information presented to them and had more calibrated expectations of the capability of Level 2 partial automation (the term calibration describes the participant's expectation of the technology aligning with its actual capabilities). Consequently, 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 did not want detailed information and expected the automation to be more capable and were less willing to work with the system. One LIP participant said, "*I want to see where my friends are and chat with them*". Not all wanted experiential features, with some saying, "*It [the vehicle] should only tell me if I need to take over control*".

The groupings were decided by two qualitative researchers who collaboratively reviewed the codes together. Out of the 25 participants, 15 were categorised as HIP and 10 as LIP. This was despite all participants being given the same description of the capabilities of Level 2 partial driving automation.

Table 5 below indicates how information preferences changed with respect to each simulated driving event, depending on whether the driver was classified as HIP or LIP. To illustrate the relative group sizes, the frequency counts for the relevant codes for each event and participant group are indicated.

There was no difference between HIP and LIP drivers for events 1 and 5 (manual driving). However, for the partially automated driving events (2, 3 and 4), HIP drivers wanted the relevant secondary safety information in order to support the vehicle; whereas LIP drivers preferred to have either tertiary or primary, but not secondary information. For example, one HIP driver in the traffic light event said, "*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*". Across events 2, 3 and 4, codes related to HIP drivers were more prevalent than those for LIP drivers.

An overall summary of the two groups are presented below in Table 6.

Table 5
Change in information preferences for High Information Preferences and Low Information Preferences drivers.

Events	1 Handover	2 Traffic	3 Junction	4 Steady State	5 Handover
HIP	Primary (f = 179)	Secondary (f = 190)	Secondary (f = 196)	Secondary (f = 152)	Primary (f = 146)
LIP		Tertiary/ Primary (f = 40)	Tertiary/ Primary (f = 48)	Tertiary/ Primary (f = 46)	

Table 6
Driver expectations observed in the data.

High Information Preferences	Low Information Preferences
• Wanted detailed information on the vehicle's situational awareness etc. • More accepting of the limitations of L2 driving automation and wanted to work with the system. • More concerned with secondary information	• Wanted less information on the status of self driving and not concerned with assisting the system • Wanted the vehicle to offer assistive features • More concerned with either tertiary or primary information

4. Discussion

The discussion follows the structure of the questions asked of participants after each driving event, finishing with how driver expectations affected information preferences.

4.1. What information would you expect to see?

4.1.1. Communication of the vehicle's situational awareness

All participants were concerned with the need to display information about the traffic conditions and the environment ahead. This is consistent with prior studies that found that feedback from the vehicle has been shown to help drivers create mental models of what the vehicle is doing and predict how it will behave (Endsley, 2016; Kieras and Bovair, 1984) and has also been found to positively affect driving style and behaviour (Gonder et al., 2012; Mullen et al., 2015). Overall, feedback is an important aspect in developing trust and acceptance (Oliveira et al., 2019).

Throughout the events, participants requested situational awareness information during automated driving, but less information presented when required to take back control, owing to a concern among participants that the information presented should not be distracting, "*I want it [notifications in the car] to be less distracting*". This was consistent with studies that have found in-vehicle tasks to impair driving performance with most serious car crashes involving driver inattention (Beanland et al., 2013; Horberry et al., 2006). This may explain why participants felt that the addition of more information during manual driving could be detrimental, but beneficial during automated driving.

4.1.2. Communication of the state of handover

Across all driving events, participants requested an automated driving indicator in the vehicle in the form of a visual light or icon. They wanted to know exactly when the handover will occur and whether the driver or vehicle will have to take control, "*I need the car to tell me if I'm allowed to self drive*". This has also been identified as a key factor in issues such as mode confusion (where the driver does not recognise which mode the vehicle is currently operating in) (Endsley, 2017; Lee et al., 2014; Shaikh and Krishnan, 2012). Transparency and clear communication with the user were highlighted as solutions to this, however, Furukawa (2013) found that even with enough information displayed, the driver may not be able to process this (Furukawa et al., 2003).

A specific notification of handover back to manual was requested by all participants. There is a question though as to how this should be presented to the user. Visual indicators have been shown to be 100% detectable by drivers but elicit slower reaction times in comparison to multi-modal warnings such as visual tactile (Lylykangas et al., 2016). This is important because it has been found that the efficacy of an automated vehicle intervention is reduced without a warning, with most drivers acting against the automatic intervention that was aiming to prevent an accident (Schieben et al., 2014). It is also important to note that once automated driving was activated, participants did not want any additional information on the communication of handover, aside from the aforementioned visual indicator.

4.2. When would the information be presented?

4.2.1. Information should be presented intelligently, or all of the time

Participants were split over having information presented all of the time (f = 12) "*I want the information presented at all times, the situation can change and I can decide if I still want to use it.*" as opposed to having information presented intelligently (f = 13) "*I want it to be least invasive*". Intelligent presentation of information would require a more comprehensive understanding of how the driver's information preferences change depending on the context. Overall, once the vehicle was returned to manual control, participants (f = 15) asked for comparatively less information. This in line with the literature on partially automated vehicles which says that providing more information can help prevent driver inattention (de Winter et al., 2014; Helldin et al., 2013). The exception was information on the vehicle's situational awareness, which was requested at all times by 13 participants during both automated and manual driving. The communication of the state of handover should only notify the user in abnormal conditions (i.e. whenever the vehicle is unsure of the current driving event). This could be because the awareness of surroundings benefits both the automated driving mode and manual driving, hence can be presented at all times. Whereas the handover status is exclusive to the automated driving mode, with participants opting to have it displayed only when necessary.

4.3. Where would the information be presented?

4.3.1. Information should be located in existing interfaces

Participants responded with an approximately even split across all driving events between the centre console (f = 43) "*I find it's* [the centre console] *in my natural eye line,*" and a digital dashboard display (f = 42) "*… because it's* [the dashboard] *where everyone looks anyway*". It is likely that participants suggested interfaces they were most familiar with. The other finding was that participants did not change their preferred information display location throughout the study, so there was no observable effect on the information display location and the driving events. Further experimental studies are required to understand where best to display information.

4.4. How would the information be presented?

4.4.1. Visual indicators with spoken auditory notifications

Across all events and participants, visual icons were requested in the vehicle along with an auditory notification to accompany it. In terms of auditory design, all participants (f = 25) preferred a spoken audio notification over a generic auditory notification sound, "*I just find spoken voices are just easier to understand*". Frequently, participants felt that spoken notifications are easier to understand in comparison to a generic auditory sound. Some participants were often concerned with being startled or annoyed by the notification (f = 9), though this may be required in a partially automated vehicle in order to demand attention and prompt a response from the driver.

4.5. How would you expect to interact with the information?

4.5.1. Limited interactions are expected when the vehicle is in automated mode

Some participants (f = 13) expected to have no interaction during automated driving, aside from any abnormal conditions, "*I don't expect to have to interact with the vehicle during self driving [automated driving]*". This correlates with the findings of the other categories, namely with the information timing, which found that either information is presented in abnormal situations or all the time. Another suggestion (f = 18) was the ability to change the driving style or speed, for example, having the option to tell the car to speed up to catch a green traffic light.

This would suggest that drivers would want to engage in secondary tasks while the automated driving is active. This supports the idea of a more intelligent interface that can provide appropriate information to support the driving task, whilst also providing secondary tasks to engage the driver.

4.6. Driver expectations and their effect on information preferences

One of the key findings from this study is the discovery of two driver categories of expectations (HIP and LIP) and its impact on information preferences. The frequency counts in Table 5 provided evidence for the groupings of participants around their information preferences. To illustrate this, participants grouped as HIP produced approximately four to five times as many codes for information preferences compared to the LIP group for each event.

Reviewing how information preferences changed depending on the driving events, there was no difference between the two groups of driver expectations when the vehicle was in manual control; the differences were only apparent once the partially automated vehicle was in control. Given that there was no difference between participants during manual driving, this indicates that current interface design practices for manual driving are inapplicable to interfaces that can support partially automated driving. Yet many of the interfaces in partially automated vehicles today are designed using manual driving interface practices to support partially automated driving (Olsen, 2018), which this study has shown to be problematic.

Overall, these results suggest that while LIP drivers are willing to work with the system to take back control if required, they were not happy to monitor safety information to ensure it was able to operate correctly-as is required with Level 2 driving automation. The issue is that regardless of these two driver categorisations and information preferences, by definition, Level 2 partial automation requires the driver to pay attention at all times during automated driving. However, as previously discussed, it is well understood that humans are ineffective at monitoring automated processes (Dzindolet et al., 2003; Kaber and Endsley, 2004; Sheridan, 1995) and this has been shown to cause riskier driver behaviour (Banks et al., 2018). When considering interfaces in partially automated vehicles today, for example, the aforementioned Tesla Autopilot system, the interfaces in those vehicles do not show recognition for the differing expectations of drivers and hence their changing information preferences. This paper has shown how partially automated driving expectations can vary significantly between users and this can affect the information and capabilities they expect in the vehicle.

The results suggest that LIP drivers will need careful consideration about how the information is presented to them in order for them to safely using partial driving automation. HIP drivers are arguably 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 interfaces, those that can adjust interface elements depending on the driving event, may be the solution to catering to differing driver preferences and expectations (Alhazmi et al., 2015; Birrell et al., 2016; Tchankue et al., 2011).

4.7. Limitations

As a result of simulator availability, the participants sampled were limited in their representation of society and were all related to the University environment. However, the study provides a basis for future work to collect more representative results.

4.8. Methodological recommendations

When reflecting on the participant responses, many of the ideas expressed were typically based around existing interfaces they were

familiar with. This may be because the BUC participants were sat in was too high in fidelity and hence was more difficult for them to suggest changes. This phenomenon had been previously observed in prototype testing, high fidelity products appear too 'complete' and hence users may struggle to suggest ways to improve upon it (Hall, 2001; Rudd et al., 1996). Deploying a lower fidelity vehicle interface may enable participants the 'freedom' to suggest more changes and ideas.

5. Conclusion

This study has demonstrated how a driver's expectations of partially automated vehicle capability can have a large effect on their informational preferences in the vehicle. Primarily, the study contributed to the preliminary identification of two driver groups: High Information Preferences (HIP) and Low Information Preferences (LIP) drivers; and a recognition that different driver types affect information preferences during different driving events. For example, LIP drivers preferred either tertiary or primary information during automated driving and were not willing to work with the system's secondary information. Conversely, HIP drivers preferred more secondary information to work with the system and ensure its correct use.

Communication of the vehicle's situational awareness and the state of handover were the most salient pieces of information for the group sampled. Intelligent presentation of information was recommended, and participants preferred the information in locations they were familiar with in vehicles today.

If future HMIs in vehicles fail to recognise that expectations in automation capability vary between drivers and that this consequently effects their information preferences, then interfaces may not provide the appropriate support. This has been found to be evident in Level 2 automated driving available today. Driver groupings and their resultant effect on the information that should be displayed is a result that warrants further investigation with a broader sample group in order to offer more generalisable results.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.apergo.2019.102969.

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