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Using Glance Behaviour to Inform the Design of Adaptive HMI for Partially Automated Vehicles

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***Abstract*— Partially automated vehicles present a large range of information to the driver in order to keep them in-the-loop and engaged with monitoring the vehicle's actions. However, existing research shows that this causes cognitive overload and disengagement from the monitoring task. Adaptive Human Machine Interfaces (HMIs) are an emerging technology that might address this problem, by prioritising the information presented. To date, research aiming to define the driver's glance fixation behaviour in a partially automated vehicle to contribute towards an adaptive interface is scarce. This study used a unique three-day longitudinal driving simulator study design to explore which information drivers in a partially automated vehicle require. Twenty-seven participants experienced nine partially automated driving simulations over three consecutive days. Nine information types, developed from standards, previous studies and industry collaboration, were displayed as discrete icons and presented on a surrogate in-vehicle display. Unique to the literature, this study showed that the recorded eye-tracking data demonstrated that usage of the information types changed with longitudinal driving simulator use. This study provides three key contributions: first, the longitudinal study design suggest that single exposure HMI evaluations may be limited in their assessment. Secondly, this study has methodologically shortlisted a list of nine information types that can be used in future studies to represent future partially automated vehicle interfaces. Finally, this is one of the first studies to characterise glance behaviour for partially automated vehicles. With this knowledge, this study contributes important design recommendations for the development of adaptive interfaces.**

***Index Terms*— adaptive HMI, interface, partially automated, vehicle, eye tracking**

I. Introduction

THE recent developments around vehicles with partial and conditional automation have raised awareness for the potential benefits the technology could bring to drivers, such as more convenience and a better user experience [1]. There is increasing market interest in partially automated driving technology [2], such as Tesla's Autopilot system. However, at SAE Level 2 driving automation, the driver is responsible for the Object and Event Detection Response (OEDR) and are the Dynamic Driving Task (DDT) fallback in situations where the automated system may fail [3], this introduces new challenges for drivers and the vehicle's human machine interface (HMI).

In partially automated vehicles, HMI design becomes more crucial to the ability of a driver to safely operate the system [4], namely around ensuring the driver remains in-the-loop and ready to take over driving control when notified [3]. Usability of vehicle systems and interfaces at any level of automation is essential. However at higher levels of automation, where responsibility for aspects of the driving task can be shared, understanding an interface and learning to interpret and interact with it quickly and effectively transitions from a user experience issues into a safety priority for both the vehicle's occupants and other road users [5]. However, it has been suggested that a large proportion of users learn to use current automated systems through trial and error; rather than through the information provided by the vehicle's HMI [6], [7].

The evidence would suggest that interfaces in partially automated vehicles today are not effective in facilitating this learning process and have been attributed as a cause in recent accidents [8]. Current HMI's in partially automated vehicles present a large variety of information to the driver, with the expectations that the information will be useful and keep the driver informed and in-the-loop [9]. However, too much information is presented in HMIs, resulting in drivers falling out-of-the-loop and disengaging with the monitoring task [10], [11].

Adaptive interfaces, those that can automatically adapt the information presented to drivers, have been suggested as a solution to ensuring drivers remain in the loop [12] by carefully managing the information presented to the driver to avoid issues of cognitive overload and distraction [13], [14]. However, questions remain as to what information should be adapted, and what drives this adaption.

A. Adaptive Interfaces for Partially Automated Vehicles

The fundamental solution being proposed by this next generation of HMIs is to reduce the number of concurrent pieces of information displayed. 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

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more appropriate for that particular instance, to increase in visual prominence in its place.

There are two approaches to this [15]: the aforementioned adaptive interface, and an adaptable interface. Though phonetically similar, an adaptable allows the user themselves to define the information they wish to be presented with. There is a lower risk of an adaptable interface presenting the wrong or inappropriate information, as the user is always in control, but the user may not be the best judge of the information they require to achieve optimal performance [16], [17]. Differing driver preferences may mean some choose to inhibit the presentation of key safety information, as was found in previous work by the authors [4].

Conversely, an adaptive interface is automatic in its selection of information. But the driver of information change is less clear [18]. There have been a number of suggestions as to what should influence the information should adapt, such as driver performance and driver modelling [19]. This would require measuring and quantifying the driver performance, then comparing this against a standard or expected level. 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 is another suggested metric [20], [21] and shares similar challenges to physiological measures [19], [22] in creating an accurate and reliable measure of these metrics. Some concepts have attempted to identify abnormal stress and workload in the user and adapt the HMI accordingly [23]. The driving scenario and environment, could also be used to drive the adaption of information [4].

Temporal effects have been recognised in other contexts of human-machine interactions. For example, drivers of electric vehicles develop more strategies for eco-driving as they become more familiar with the system over time [24]. However, these factors have been largely overlooked [25], [26]. This Similarly, trust in automated vehicles, has been shown to be a dynamic process that changes over time [27]. User evaluations of service usability has also been shown to be affected by longitudinal experience [28].

Most significantly to this research, the temporal effect of the driver's developing experience with the system has been found to have a significant effect on the information drivers used during partially automated driving [29]. Naturally, questions still remain around how the information should be graphically adapted on a display. Visual prominence is a measure of how easily a user can access the information on an HMI and 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 [30]–[32]. However, for this study, understanding how visual prominence should change was out of the scope. Rather, it was argued that first a better understanding of *what* information needs to be presented must be achieved, before questions around the graphical implementation on an HMI can be addressed.

B. *Eye Tracking*

The tool used to quantify the usage of information was eye tracking. Eye-tracking has been used to as a measure of a person's visual attention [33]. In recent times, eye tracking has become more frequently used and consequently there has been a focus on how more readily available technology can be used to facilitate eye-tracking, such as webcams [34] and mobile apps [35]. In the automotive context, eye tracking has been used to assess HMI against measures such as Total Eyes Off-Road Time (TEORT), Long Glance Proportion (LGP) and Mean Single Glance Duration (MSGD) [36]–[39]. Another common metric is the assessment of glance behaviour to the roadway [40], [41].

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 [42], [43], educational diagrams [44] and advertising effectiveness [45].

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.

From a technical perspective, eye-tracking records a series of gaze points, which can then be grouped into several different measures; the most common being fixations and saccades [46]. Of interest to this study are fixations; which are groupings of gaze points that are aggregated around a particular area and are of a specific length of time.

The minimum duration of aggregated gaze points is an area of debate. A lower limit of 200ms has been used to determine the point at which an aggregation of gaze points become a fixation [46], [47], though these are largely derived from work from 1962 [48]. Hence, some have suggested that a fixation threshold of 200ms is too restrictive and cognitive understanding can be achieved in as little as 100 ms [49]–[51]. This is especially true in the context of automotive HMI [47], [50].

The eye-tracking hardware can also impact that data. The recording frequency (measured in Hertz, Hz) determines the number of gaze points recorded every second, with these values ranging between 20-2000 Hz [52]. Hence, a higher recording frequency will capture more data which can be fed into a better understanding of glance location.

Hence, with adaptive interfaces being a possible solution to the HMI challenge of partially automated vehicles, the focus of this paper was to address the gap in fundamental knowledge regarding what information could and should be adapted over time to better support the driver. The opportunity was identified to develop an understanding of the design requirements for such an interface by defining how glance behaviour changes with increasing familiarity with a partially automated system, during steady state and driving events. For this study, steady state refers to driving automation where the vehicle is operating appropriately within its design domain. Driving events were defined as any scenario where the driver may be required to intervene and take control from the partially automated system

C. Aim

This study aimed to longitudinally understand the glance behaviour for drivers of partially automated vehicles following handover and warning events, to inform the design of an adaptive interface.

D. Objectives

This study addressed the aim by:

1) Measuring the overall percentage of time participants spent fixating on the information display
2) Measuring the change in fixations to each information type as the driver becomes more familiar with the system
3) Measuring the change in fixations to each information type after handover events
4) Measuring the change in fixations to each information type after warning events

II. Method

A. Study Design Summary

This study took part at WMG, University of Warwick, United Kingdom.

The experiment followed a three consecutive day, within subjects experimental design with a total of nine unique driving simulations presented to each participant. On each day a participant was presented with three driving simulations between 6-10 minutes long. For each driving simulation, an interface was presented that displayed nine information types in a 3x3 grid on an iPad Pro surrogate display (Figure 1). The information presented in the 3x3 grid was counter-balanced according to a Latin squares experimental design.

Eye tracking glasses were used to measure the number of fixations to each information type on the surrogate display. This enabled the analysis of glance behaviour.

B. Participants

In total, 27 participants were recruited for this study (14 Male; 13 Female). Participants age was reported in age brackets as follows: 10 (18-24), 13 (25-34), 1 (41-50), 3 (71-80). The mean age of participants was 32.3 years, with a standard deviation of 16.6. None of the participants had prior experience of using an automated vehicle. Participants were recruited through email and poster advertising around the local area of Coventry and the University of Warwick (UK). Any participant who held a valid driving license (UK/EU or International) and was over 18 years old was eligible to partake in the study. Participants who wore glasses were excluded from the study as this would have interfered with the eye tracking glasses.

Participants were paid £5 per session attended and an additional £5 for completing all sessions. This meant a participant who completed all three sessions was paid £20 in total. All participants were able to complete all three days of simulations.

C. Materials

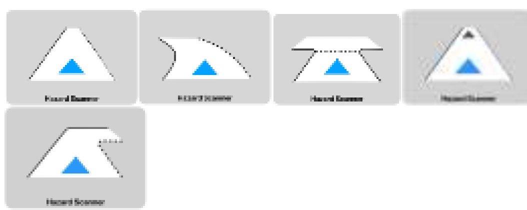
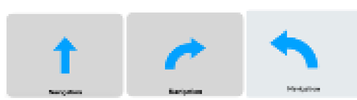
1) Selection of Information to Display

There are a wide range of possible information types that could be presented inside a partially automated vehicle. In order to create an interface that could be considered representative of future partially automated vehicles, a methodological approach to shortlisting information was taken. First, numerous vehicle HMI information standards, such as BS EN ISO 15008:2017 [53] and ECE 121 [54] were referenced to build an initial list of potential information types. Then, existing interfaces in partially automated vehicles today were reviewed [9]. Furthermore, results from previous work from the authors contributed towards this shortlist [4]. This resulted in 30 types of information for presentation inside a partially automated vehicle. However, this would be too many to practically present in a vehicle. Hence to ensure a balanced spread of information, the shortlist was then categorised against three theoretical models:

1) The Skills, Rules, Knowledge (SRK) model by [55], organised information according to its cognitive demand. Information considered to be of an automatic, learned response was classed as Skill (Sk). Information requiring the driver to interpret information then follow a familiar action was considered Rule (Ru). Finally, information requiring the driver to develop a mental model of the information, then draw comparisons to the environment was considered Knowledge (Kno).
2) The Primary, Secondary, Tertiary (PST) model [56] organised information according to its role in the driving task. Information related to the vehicle's primary control was classed as Primary (P). Information related to increasing the safety of the vehicle was Secondary (S). Finally, information related with non-critical information systems was classed as Tertiary (T). However, the model was originally intended for vehicles with no automated capability, some information specific to partially automated vehicles was difficult to categorize into the model.
3) The Trust Model (TM) by [57], organised information according to its role in the development of trust. The model describes two factors: System Transparency (ST) (defined as communication of the future state of the vehicle) and Technical Competence (TC) (defined as communication of the current state of the vehicle). The model describes a third category, Situation Management; however, this was not applicable to this study as it was focussed on steady-state driving scenarios. The key difference between System Transparency and Technical Competence, was that System Transparency information enabled the driver to act proactively to intervene with the system's operation before an action occurred. In comparison, Technical Competence information presented what was happening currently, hence did not allow for preventative action.

In order to categorise the information against these three models, informal workshops were held between academics from University of Warwick and industry HMI professionals from Jaguar Land Rover. Through card-sorting exercises, the initial 30 information types were reduced to nine that were presented in the study (Table II). These exercises involved

TABLE I
COMPLETE LIST OF INFORMATION STATES

Information	Steady State	Warnings	Handover Events
Action Explanation	"Following GPS Route Guidance" "Very heavy traffic, following GPS route guidance" "Merging to join motorway, following GPS route guidance "Arrived"	"Warning! Outside temperature below 5 °C" "Please be ready to take over control. Roadworks detected after motorway." "Please take over control. Lane markings not found"	"Please take over control now" "Vehicle in manual control"
Auto Indicator		No change	
Battery	Steadily decreased accordingly		
Energy Usage	Fluctuated in response to the acceleration of the vehicle		
Hazard Scanner			
Navigation			
Road Signs			
Traffic			
Vehicle Warnings			

deliberation on each information type and how it should be categorised. This was carried out and refined across three different meetings.

2) Interface Design

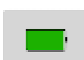
The interface for the study was designed and programmed using Sketch (version 52.6) and Hype 3.

A key question to be addressed was around the visual salience of the information icons designed. It was evident that visual salience is more dependent on the relative similarities or dissimilarities of the icons, rather than any specific attribute values (such as individual colour or design) [58], [59]. Hence, the use of specific colours in the icons (such as green or red) may not necessarily make the icon more visually salient, if other icons are equally visually salient.

However, prototyping was still used to ensure a balance in visual salience. Tachistoscopic presentation [60] was used as part of a pilot study with five researchers at the University of Warwick who had no prior knowledge of the information icons or the study. The interface was flashed to the testers for a period of 200ms, with icons varying in position. Eye tracking glasses were used to measure the glances to the interface. The prototype testing found no visual salience imbalances for the information types. Any remaining visual salience imbalances that were not evident in this testing phase were expected to be mitigated by the unique three-day longitudinal design of the study.

Table I shows the information alongside its final icon representation and how each was categorised according to the three model (Sk = Skills, Ru = Rules, Kno = Knowledge; P = Primary, S = Secondary, T = Tertiary; TC = Technical competence and ST = System Transparency.)

TABLE II
INFORMATION FOR STUDY INTERFACE (WHERE SK=SKILLS, RU= RULES, KNO= KNOWLEDGE; P=PRIMARY, S= SECONDARY, T=TERTIARY; TC= TECHNICAL COMPETENCE, ST= SYSTEM TRANSPARENCY)

Information	Icon	Description	Category
Action Explanation		Described the vehicle's actions in a descriptive statement	Ru/P/TC
Automated Mode Indicator		Indicated whether partially automated driving 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. (eg. Would increase during acceleration)	Kno/T/TC
Hazard Scanner		Revealed hazards in the roadway. Allowed the driver to confirm 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 upcoming road sign, allowing 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

While the function of most of the information types are relatively self-explanatory with the aid of Table II, Action Explanation was felt to warrant further detailing. The design of this information was based on the results of previous work by the authors [4]. The information sought to provide drivers with an explanation as to what was happening, and why (where applicable). An explanation as to what was happening and why, has also been identified as a key aspect in the successful use of an automated driving system [61].

Table II illustrates a selection of the varying states for each of the information icons. These icons changed and updated dynamically in accordance to the driving simulations, replicating a live interface inside a partially automated vehicle.

Figure 1 shows the final interface displayed the icons on the surrogate information display, next to the steering wheel. The icons were presented according to a balanced Latin squares arrangement. For nine icons, this meant 18 combinations of icons. Hence, given that each participant received 9 simulations, participants were presented with one of two blocks of icon arrangement.

3) Apparatus

An iPad Pro 2018 featuring a 10.5-inch display with a resolution of 2224 by 1668 pixels was used as a surrogate for the vehicle's dashboard display, displaying the nine information types to participants. Tobii Pro 2 eye-tracking glasses were used to record participant glances towards the nine information types on the iPad display. The Tobii Pro 2 recorded at 100Hz with a 1920x1080, 25 frames per second video resolution and an 82° horizontal, 52° vertical field of view. This high level of recording fidelity contributed to the reliability and accuracy of the recorded glances.

The Tobii Pro 2 glasses were connected to a mobile recording unit using a HDMI cable. Recording was controlled wirelessly through a Microsoft Surface.

For this study, fixations were chosen as the primary metric for analysis. This is because fixations are a series of gaze points that are fixed in a particular location, as the foveal vision processed the information being looked at [62]. This measure has been frequently used in the context of automotive human factors studies [63]. Furthermore, the aim of this study was to understand the usage of information. As will be detailed later, all eye tracking must make the eye-mind assumption (that a point being visually fixated is being actively cognitively processed). Hence, for this reason, fixations were considered the most appropriate measure for this study.

4) Driving Simulation

The WMG 3xD Development Simulator was used for the study using software developed by XPI Simulation. The simulator used a three-screen immersive setup, as can be seen in Figure 1.

Figure 1 WMG 3xD Development Simulator, with an iPad positioned as a surrogate center console display

A detailed description of the driving simulations can be seen in Table III.

A total of nine simulations were presented over the three trial days. Six of the nine simulations featured steady state driving with no driving event. The remaining three simulations featured driving events:

1) Planned Handover (with a Planned Handover Warning) (PH and PW)
2) Emergency Handover (EH)
3) Temperature Warning (TW)

Participants were given only steady state scenarios on the first day, to allow for simulator acclimatization. The remaining six scenarios were presented over the course of the remaining two days at random.

Both the planned handover warning and planned handover were presented in the same simulation, analogous to the likely order of events in a real life planned handover simulation, requiring the participant to take over control two minutes after receiving a handover warning. The emergency handover required the participant to take control of the vehicle when warned immediately. The final event was a temperature warning that warned participants that the outside temperature was below four degrees.

TABLE III
DESCRIPTION OF SIMULATIONS

Sim.	Description	Duration
1	Motorway driving with no handover	8 minutes
2	Motorway driving with no handover	9 minutes
3	Rural driving with no handover	5 minutes
4	Rural driving with no handover	6 minutes
5	Town centre driving with no handover	7 minutes
6	Town centre driving with heavy traffic	8 minutes
7	Steady state motorway driving with a planned handover. ***Planned Handover Warning*** *presented two minutes before handover alterting driver that a handover will occur after motorway because of roadworks. No driver action required.* ***Planned Handover*** *occurs after exiting motorway. Driver must take control of vehicle and manually drive for 1 minute*	8 minutes
8	Steady state rural driving with an emergency handover. ***Emergency Handover*** *where no prior warning was given, and the participant must immediately take control of the vehicle at the end of the simulation. They then drive manually for 1 minute.*	10 minutes
9	Steady state town centre driving ***Temperature Warning*** *warns participant of low temperatures after 3 minutes. No driver action required.*	7 minutes

The aim of the experimental design was to achieve a simulation exposure time per participant per day of approximately 25-30 minutes. This is in line with the average commuting durations for travel by personal cars [64].

D. *Procedure*

Participants were invited into the simulator room and informed consent was received. Participants were asked to observe the vehicle operating in a partially automated driving mode and use the information presented to them in any way that made them feel comfortable in the use of the system. Participants were advised that the vehicle was partially automated and consequently they may be required to take over control from the system at any time. While they were not required to keep their hands on the steering wheel, they were told to continuously monitor the vehicle's operation and intervene if they felt it was appropriate to prevent an accident or issue.

Given the unique longitudinal design of the study, it was expected that participants would have the chance to also learn the system through trial and error, particularly on day 1. For this reason, on day 1, only randomised *steady state* simulations were presented. This allowed participants to acclimatise to the simulator environment on the first day and understand how the vehicle operates in steady state conditions. On days 2 and 3, steady state and event simulations were presented randomly across the remaining sessions. Between simulations, participants were given a five-minute break and offered refreshments. Eye-tracking calibration was repeated, and the participant then completed the second, then third simulations. At the end of the session, a time for the next session on the following day was agreed. All participants completed their sessions at the same time each day to mitigate confounding effects between the days.

The Tobii Pro 2 Glasses were calibrated before every session (i.e. calibrated three times per participant, every day).

E. Data Analysis

The primary data collected was the number of fixations to each individual information icon on the iPad surrogate dashboard display. Fixations were detected using the algorithm provided by Tobii, called I-VT Filter (Fixation) [65]. This algorithm limited fixations to a minimum threshold of 60ms in length. Previous studies have found that fixations as low as 35ms are long enough for 75% accuracy when reading road signs [66]. This is corroborated by other studies that have also suggested sub-200ms minimum thresholds, such as 60ms [65], [67].

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. Data normality for the entire week's data was calculated using the Shapiro-Wilks test. Consequently, a 9-level Repeated Measures ANOVA was carried out. Post-hoc pairwise comparisons with the Bonferroni correction was 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. 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 both handover and warning events was calculated by calculating the percentage change after the event compared to the average fixations during one minute of steady-state driving. All fixation data before an event occurred was considered steady state. This was then normalised for one minute, to allow for the comparison of fixations after the driving event. Paired t-tests were used to test for statistically significant differences between the steady-state one minute average and the post-event fixations. Significances were corrected using the Holm-Bonferroni correction.

III. Results

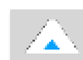
This study aimed to define the glance fixation behaviour for drivers of partially automated vehicles, to inform the design of an adaptive interface. The results for each of the objectives described in the introduction will be presented in turn.

Tobii Pro Lab software reported a recorded gaze samples percentage of 99%, indicating the tracking of participant fixations was successful.

A. Overall Steady State Fixations to each of the Information Types

Overall, participants spent 3.45% of their time fixating on the information display. Table IV 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 IV
AVERAGE TOTAL FIXATIONS FOR EACH INFORMATION TYPE DURING STEADY STATE

Information	Icon	Average number of fixations for the whole week per participant	Average single fixation duration (s)
Action Explanation		*M* = 109 *SD* = 13.9	*M* = 0.183 *SD* = 0.04
Automated Mode Indicator		*M* = 106 *SD* = 15.2	*M* = 0.181 *SD* = 0.05
Battery		*M* = 83.5 *SD* = 8.75	*M* = 0.163 *SD* = 0.03
Energy Usage		*M* = 67.8 *SD* = 10.9	*M* = 0.187 *SD* = 0.07
Hazard Scanner		*M* = 103 *SD* = 10.9	*M* = 0.198 *SD* = 0.04
Navigation		*M* = 98.9 *SD* = 9.64	*M* = 0.176 *SD* = 0.03
Road Signs		*M* = 109 *SD* = 11.4	*M* = 0.173 *SD* = 0.03
Traffic		*M* = 49.1 *SD* = 6.35	*M* = 0.195 *SD* = 0.04
Vehicle Warnings		*M* = 56.1 *SD* = 8.07	*M* = 0.171 *SD* = 0.04

Action Explanation was the most fixated on information types (*M* = 109, *SD* = 13.9). Road Signs also exhibited a high number of fixations (*M* = 109, *SD* = 11.4), followed by the Auto Indicator (*M* = 106, *SD* = 15.2) and Hazard Scanner (*M* = 103, *SD* = 10.9). The least fixated on information was Traffic (*M* = 49.1, *SD* = 6.35).

A Repeated-Measures ANOVA with a Greenhouse-Geiser correction reported a significant difference between the mean total fixations to the information types ($F(3.332, 86.830) = 7.210$, $p = 0.001$). Post hoc tests using the Bonferroni correction found that Traffic (*M* = 49.1, *SD* = 6.35) and Vehicle Warnings (*M* = 56.1, *SD* = 8.07) were significantly less fixated on than Action Explanation (*M* = 109, *SD* = 13.9), Battery (*M* = 83.5, *SD* = 8.75), Hazard Scanner (*M* = 103, *SD* = 10.9), Navigation (*M* = 98.9, *SD* = 9.64) and Road Signs (*M* = 109, *SD* = 11.4).

This indicated that Traffic and Vehicle Warnings were the least fixated on information types.

A Repeated-Measures ANOVA with a Greenhouse-Geiser correction reported a significant difference between the average single fixation lengths ($F(4.098, 106.549) = 4.308$, $p = 0.029$). Battery ($sM = 0.163$s, $sSD = 0.03$s) (where sM = mean single fixation and sSD = standard deviation of mean single fixation) attracted significantly shorter single fixations on average than the Hazard Scanner ($sM = 0.198$s, $sSD = 0.04$s), Navigation ($sM = 0.176$, $sSD = 0.03$s) and Traffic ($sM = 0.195$, $sSD = 0.04$s). Action Explanation was found to have no significant differences in average single fixation length compared to the other information types.

B. Change in fixations during steady state driving

Table V and Figure 2 shows the average number of fixations to each information type for each day of the trial week.

TABLE V
AVERAGE FIXATIONS TO EACH INFORMATION TYPE FOR EACH TRIAL DAY DURING STEADY STATE (BOLD RESULTS INDICATE SIGNIFICANCE P < 0.05)

Information	Day 1	Day 2	Day 3	Friedman, Wilcoxon and Kendall's tests
Action Explanation	$M = 13.9$ $SD = 11.2$	$M = 9.80$ $SD = 7.07$	$M = 12.4$ $SD = 9.63$	$\chi^2(2) = 2.598$, $p = 0.273$ $W = 0.048$
Automated Mode Indicator	$M = 16.7$ $SD = 15.8$	$M = 10.1$ $SD = 11.1$	$M = 8.55$ $SD = 8.76$	**$\chi^2(2) = 12.906$, $p = 0.002$ Day 1 and Day 2, 3 ($p = 0.006, 0.002$), $W = 0.239$**
Battery	$M = 12.5$ $SD = 8.36$	$M = 7.68$ $SD = 5.71$	$M = 7.63$ $SD = 4.15$	**$\chi^2(2) = 10.491$, $p = 0.005$, Day 1 and Day 2, 3 ($p = 0.006, 0.002$) $W = 0.194$**
Energy Usage	$M = 9.82$ $SD = 5.91$	$M = 6.19$ $SD = 4.90$	$M = 6.61$ $SD = 5.89$	**$\chi^2(2) = 15.360$, $p = 0.000$, Day 1 and 2,3 ($p = 0.003, 0.008$), $W = 0.284$**
Hazard Scanner	$M = 12.3$ $SD = 8.89$	$M = 11.4$ $SD = 6.10$	$M = 10.6$ $SD = 7.46$	$\chi^2(2) = 2.509$, $p = 0.285$, $W = 0.046$
Navigation	$M = 12.1$ SD = 7.22	$M = 11.5$ $SD = 7.21$	$M = 9.35$ $SD = 7.29$	$\chi^2(2) = 4.514$, $p = 0.105$, $W = 0.084$
Road Signs	$M = 17.2$ $SD = 10.1$	$M = 9.88$ $SD = 7.37$	$M = 9.16$ $SD = 6.14$	**$\chi^2(2) = 18.250$, $p = 0.000$ Day 1 and 2, 3 ($p = 0.001, 0.000$), $W = 0.338$**
Traffic	$M = 6.20$ $SD = 4.61$	$M = 4.92$ $SD = 4.00$	$M = 5.27$ $SD = 3.85$	$\chi^2(2) = 1.390$, $p = 0.499$, $W = 0.026$
Vehicle Warnings	$M = 7.99$ $SD = 7.95$	$M = 5.74$ $SD = 6.37$	$M = 4.96$ $SD = 3.15$	$\chi^2(2) = 3.185$, $p = 0.203$, $W = 0.059$

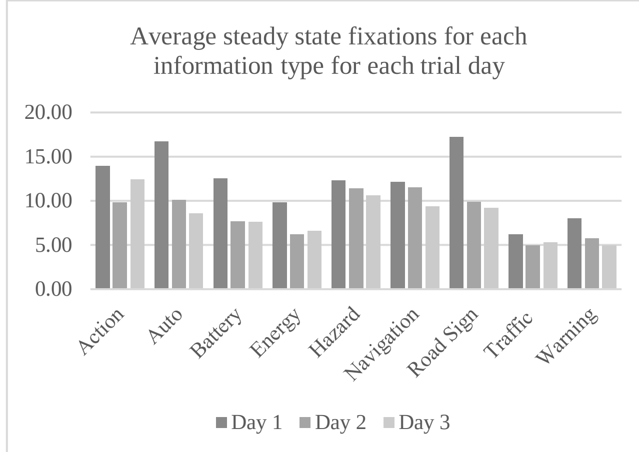
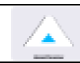
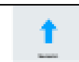
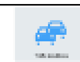
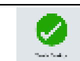


Figure 2 Change in average steady state fixations to each information type for each trial day

Data for the individual days of fixation data was not normally distributed. Significant differences in the fixation counts between the days was observed. In these cases, 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 Automated Indicator and Road Signs showed the largest decrease in fixations between Day 1 and 3 ($M\_day1 = 16.7$,

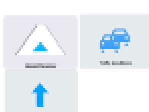
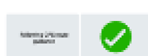
TABLE VI
CHANGE IN FIXATIONS AFTER EACH HANDOVER EVENT WITH COHEN'S D VALUES REPORTED (* DENOTES A SIGNIFICANT RESULT FROM THE PAIRED T-TESTS WITH HOLM-BONFERRONI CORRECTION, ALPHA = 0.05)

Info.	**Action Exp.**	**Auto Indic.**	**Batt.**	**Ener.**	**Haz. Scan.**	**Nav.**	**Road Signs**	**Traffic**	**Vehic.Warn.**
Abbreviation	Ac	Au	B	E	Ha	Nav	RS	T	W
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* *d* = 0.650	1.22* *d* = -0.494	1.33 *d* = -0.230	1.37 *d* = -0.500	1.26* *d* = -0.452	0.81* *d* = -0.753	0.37* *d* = -1.589	0.30* *d* = -0.708	3.44* *d* = 0.501
	+198%*	-46.8%*	-26.3%	-6.75%	-43.5%*	-62.0%*	-84.3%*	-72.1%*	+183%*
Planned Handover (ph)	3.41 *d* = 0.301	2.63 *d* = 0.113	1.81 *d* = 0.007	1.37 *d* = -0.067	0.81* *d* = -0.801	1.11* *d* = -0.634	2.11 *d* = -0.112	0.48* *d* = -0.548	0.85 *d* = -0.274
	+44.9%	+14.4%	+0.322%	-6.75%	-63.5%*	-48.2%*	-10.6%	-54.7%*	-29.9%
Planned Handover Warning (phw)	21.96* *d* = 1.891	3.48* *d* = 0.420	3.31* *d* = 0.396	3.31* *d* = 0.550	1.87 *d* = -0.221	2.46 *d* = 0.206	2.31 *d* = -0.017	2.00 *d* = 0.343	21.96* *d* = 1.456
	+834%*	+51.4%*	+83.2%*	+126%*	-16.1%	+14.9%	-2.00%	+88.1%	+520%*
Temp. Warning (tw)	4.48* *d* = 0.621	1.37* *d* = -0.623	2.33 *d* = 0.285	1.56 *d* = 0.045	2.74 *d* = 0.259	3.41* *d* = 0.484	2.44 *d* = 0.046	0.93 *d* = -0.097	3.70* *d* = 0.576
	+90.6%*	-40.4%*	+29.0%	+5.86%	+22.9%	+59.0%*	+3.53%	-12.9%	205%*

M_day3 = 8.6, *p*=0.002 and *M_day1* = 17.2, *M_day3* = 9.16, *p* = 0.000, respectively). 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 Trust Model by Choi and Ji (2015) (hereinafter TM) as was done in [29], shown below in Table VI. Results were organized into the other models previously discussed in this paper (SRK and PST), however, interpretations were less clear and it appeared that the trust model provided a clearer narrative for the change in fixations.

TABLE VII
FIXATIONS CHANGES FOR STEADY STATE DRIVING

Information	System Transparency	Technical Competence
Usage Increased		
Usage Consistent		
Usage Decreased		

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

C. Changes in fixations after handover events

Table VII shows the change in fixations after each driving event (2 handover and 2 warning events). The average steady-state fixations for one minute are listed along the top row, as calculated using the procedure described in the previous data analysis chapter. For each analysis, the steady state fixations normalised for one minute were compared against the average fixations for one minute after the event. The normalised one minute of steady state driving is comprised of the fixations for the whole steady state driving time before the event. For each event, the average number of fixations is reported and below this, the percentage change in fixations from steady-state is reported.

1) After emergency handover

The results are illustrated below in Figure 3.

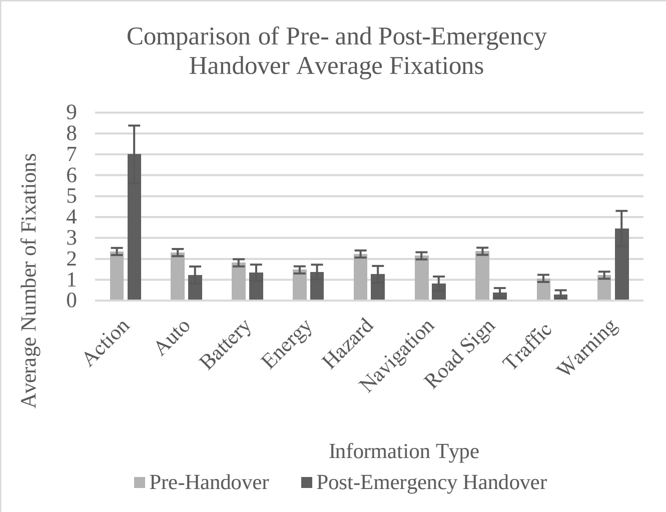


Figure 3 Change in fixations after the emergency handover

After an emergency handover, all System Transparency information decreased significantly in usage. Technical Competence information had more diverse results, with Action Explanation (+198%) pairing with Vehicle Warnings (+183%) when increasing in fixations. Battery and Energy both remained consistent. Auto Indicator fell in fixations (-46.8%).

2) After planned handover

The results are illustrated below in Figure 4.

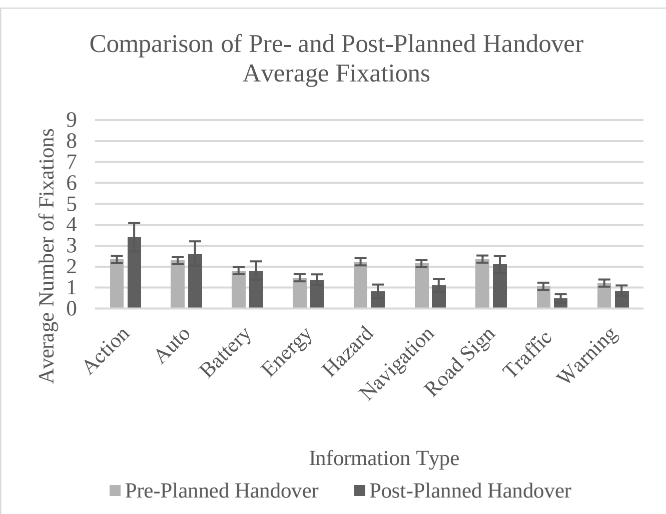


Figure 4 Change in fixations from the one minute average steady state to after the planned handover

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.

D. Changes in fixations after warning events

1) After the planned handover warning

The results are illustrated below in Figure 5. Note, the period of two minutes was normalised to one minute for this comparison.

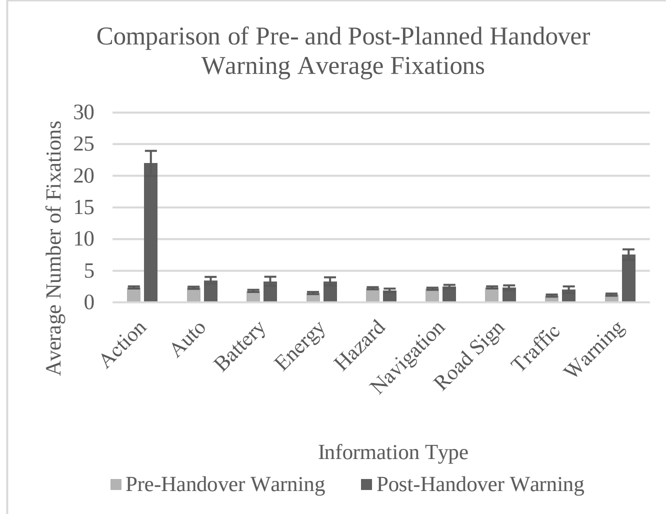


Figure 5 Change in fixations from the one minute average steady state to after the warning two minutes before the planned handover

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

2) After temperature warning

The results are illustrated below Figure 6.

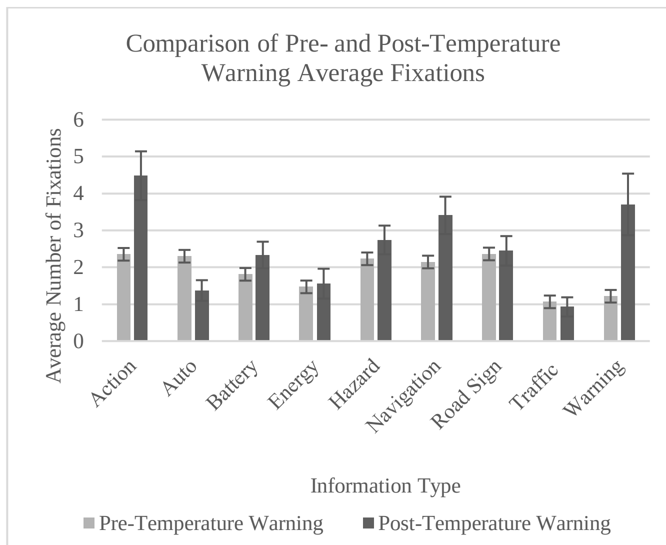


Figure 6 Change in fixations from the one minute average steady state to one minute after the temperature warning

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.

IV. DISCUSSION

This study aimed to define the glance fixation behaviour for drivers of partially automated vehicles to begin to inform the design of an adaptive interface. These results contribute to the growing body of knowledge around glance fixation behaviour in partially automated vehicles and will allow for future studies to continue to build on the study design implemented here.

A. Summary of main results

The overall percentage of time participants spent fixating on the information display was 3.45%. Traffic (M = 49.1) and Vehicle Warnings (M = 56.1) were found to be significantly less fixated on than the Action Explanation (M = 109), Battery (M= 83.5), Hazard Scanner (M = 103), Navigation (M = 98.9) and Road Signs (M = 109. Regarding the length of the average single fixation, Battery (sM = 0.163s) (where sM = mean single fixation) had significantly shorter single fixations when compared to the Hazard Scanner (sM = 0.198s), Navigation (sM = 0.176) and Traffic (sM = 0.195). Action Explanation was found to have no significant differences in average single fixation length compared to the other information types. Traffic information displayed the lowest average number of fixations, but the longest single fixation duration. It is unclear why this was the case, it may have been that when stuck in traffic, participants spent longer looking at the icon for an indication of when the traffic flow may improve.

Next, considering the longitudinal change in fixations during the steady state portion of simulated driving, all significant changes occurred after day 1 (i.e. there was no significant difference in fixations observed between day 2 and 3). 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) exhibited the largest decrease in fixations. Action Explanation, Hazard Scanner, Navigation, Traffic and Vehicle Warnings all displayed no significant differences in fixation counts across the trial week.

Action Explanation and Vehicle Warnings always increased significantly in usage or remained consistent in usage together after all of the driving events. Similarly, the Battery and Energy Usage were also paired together after driving events. After the emergency handover, all System Transparency information reduced significantly in fixations. Similarly, after the planned handover, most System Transparency information reduced significantly in fixations (with the exception of 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.

B. Implications for adaptive interface design

When considering the analytical approach to understanding the results, it was considered that there were two ways in which the discussion of results could be approached. The first would be to say that any information that decreased in fixations is of less 'importance' and should consequently be reduced in prominence on an adaptive interface. On the contrary, the approach we took recognises the importance of all the information chosen for this study, to the safe use of a partially automated system and hence highlight the need to reconsider how the information is presented to drivers to improve engagement. Hence, while glance fixation behaviour may tend away from a particular information type over the course of the week, it may still hold importance to the user. Therefore, it may be a question of adapting the information's prominence on the HMI to reflect its less frequent or decreasing use. Methodologically, these considerations are only possible as a result of the longitudinal study design by providing an overall number of fixations and an understanding of how these changed during the trial week; consequently, the methodology itself forms an important contribution to knowledge.

By synthesising the results of this study's four objectives, a more holistic understanding of glance fixation behaviour and its impact of interface design for future automated vehicles can be achieved. The next section will discuss the results of each objective in turn.

C. Overall Percentage of Time Fixating on the Information Display as a Whole

Studies that have used eye-tracking to measure fixations inside a vehicle have reported a range of percentages for the time spent looking at an in-vehicle display; such as 2.87% [29], 4.3% [40], 11.24% [68]. The figure of 3.45% reported in this study falls within a similar range as these studies, along with the average single fixation length (0.171s to 0.198s) [69], suggesting the participants exhibited analogous interface usage behaviours. It should be noted that these previous studies were based around a manually driven vehicle, as opposed to a partially automated system, which could have contributed to the lower percentage of time fixating on the information display. Evidently, monitoring of the roadway remains the preferred supervision method used by participants for partially automated operation.

Considering the Trust Model by Choi and Ji [57], this would fall under supervision of the Technical Competence (TC) of the vehicle. The System Transparency (ST) information provided by the vehicle can help a user determine if the vehicle's sensing capabilities align with what the user sees in the roadway.

Considering this value of 3.45%, in comparison to figures found for manual driving [40], this is comparatively lower. When compared to manual driving today, it may be the case that in order to process the information (for example, compare the vehicle's intended actions with the real-world conditions) that drivers may spend a longer amount of time using the information presented. Evidence would suggest, there are notable and significant differences in the information requirements between manual driving and partially automated driving [70]. Hence, as automated technology in vehicles continues to develop, the results from this study suggests that there should be consideration for the amount of time a driver should spend utilizing the HMI information, from a safety perspective.

D. Changes in Glance Fixation behaviour

The longitudinal study design enabled a deeper understanding of glance fixation behaviour inside a partially automated vehicle by considering the overall number of fixations to information types and the change in fixations over the course of the three-day study design.

This section will consider the usage changes of the information during the longitudinal steady state portions of automated driving.

All information defined as Technical Competence decreased significantly during steady state automated driving, with the exception of the Action Explanation and Vehicle Warnings. Action Explanation, was created for this study based on the results of the authors' previous work [4], [71], through a recognition that users required clear communication of the system's status. The consistent use of Action Explanation and Vehicle Warnings suggest these two information types are key for drivers during continued steady state operation. While Action Explanation presented relatively descriptive, detailed information, the non-significant average single fixation duration suggests it was no more visually salient than the other information types; and that the result is an effect of the utility of the information.

The importance of this information was also evident across the driving events that occurred (two handover events and two warning events). In all events, fixations to Action Explanation increased when compared to the average steady state fixations:

- After emergency handover, 197% increase in fixations to Action Explanation (p = 0.002)
- After planned handover warning, 833% increase in fixations to Action Explanation (p = 0.000)
- After planned handover, 44% increase in fixations to Action Explanation (p = 0.07)
- After temperature warning, 90% increase in fixations to Action Explanation (p = 0.09)

Previous studies have recognised that the explanation as to what the vehicle is doing and why, can ensure the safe use of an automated system [61], [72]. This would explain why participants consistently used this explanatory information during the vehicle's steady state operation. Specifically, Koo et al. (2015) and Körber et al (2018) both tested phrasing of information, by explaining either 'what' and 'why' the vehicle action was taking place and found improved driver performance with the automated system. In this study, Action Explanation provided a combination of what and why information in a single notification, for example, "Warning! Please take over control- lane markings not found". The results would suggest that participants tended more toward the detailed information that can explain 'what' and 'why', both during steady state driving, as there was no significant drop over the repeated simulations, and after driving events.

There were also significant increases in fixations overall to the Vehicle Warnings, alongside the Action Explanation.

- After emergency handover, 183% increase in fixations to Vehicle Warnings (p = 0.011)
- After planned handover warning, 520% increase in fixations to Vehicle Warnings (p = 0.000)
- After temperature warning, 205% increase in fixations to Vehicle Warnings (p = 0.000)

In these driving events, the Action Explanation provided a description of 'why' and the Vehicle Warnings provided an indication of 'what', indicating an issue was occurring. It is an indication that these two must be present on an HMI for a partially automated vehicle.

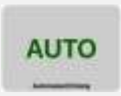
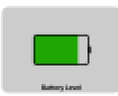
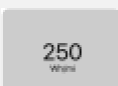
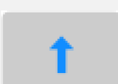
With regards to an adaptive interface that is more intelligent and selective about the information presented to drivers, the results would suggest there is an opportunity to minimise the prominence of certain information that was less fixated on during these conditions. It has been observed that locking out other information from user interaction has been found to improve driving performance in vehicles with no automation, but with reducing user acceptance [73]. However, based on this study's results, it may be possible for information to be reduced in prominence without impacting the user acceptance- as fixations were repeatedly focussed on particular information.

Another notable paring of information types was the Energy Usage and Battery level. Both exhibited a statistically significant decrease in fixations over the course of the longitudinal study design. Conversely, Energy Usage and Battery remained consistent or increased significantly after the driving events. Confirmation of vehicle range was important to participants during driving events, and it has been found that the communication of electric vehicle range is important to the development of trust in the technology [74]. Furthermore, it is notable that participants tended to use a visual icon (Battery) alongside more detailed explanations of 'why' (Energy Usage), highlighting the importance of this form of combined information presentation, not only for future automated vehicles, but also for current electric vehicles.

Navigation and Traffic both were found to be consistently used throughout the longitudinal study, but both displayed significant decreases in usage after both handover events, where control of the vehicle was ceded to the driver. It is possible that the study design may have influenced this reduction in usage, as after participants received control of the vehicle, they were only required to drive in a straight line through a low traffic simulation, reducing the utility of the information.

The Hazard Scanner was designed to closely resemble comparable information in interfaces existing today in partially automated vehicles. It exhibited no significant change in fixations over the course of the longitudinal study. The consistency of its use suggests that it remained an important information type of drivers of partially automated vehicles. These results contrast with other studies, that have found this type of information to fall significantly in usage over time [29]. However, this previous study used only steady state

TABLE VIII
DESIGN RECOMMENDATIONS SUMMARY

Information		Recommendation and Results
 **Action Explanation**	**Recommendation**	• **Give higher prominence during any event** • **Give higher prominence during automated steady-state driving**
	Justification from results	• Developed from multiple studies [4], [71] • No significant change in fixations • Increased usage in all events and was always paired with Vehicle Warnings
 **Auto Indicator**	**Recommendation**	• **Make appropriate adaptions after any event** • **Give moderate prominence during automated steady-state driving**
	Justification from results	• Developed from multiple studies [4], [71] • Decreased significantly in fixations but had high overall fixations • Varied changes in fixations after events
 **Battery Level**	**Recommendation**	• **Give higher prominence during the planned handover warning** • **Give moderate prominence during steady-state**
	Justification from results	• Key information for electric vehicles [82] • Decreased significantly in fixations but had moderate overall fixations • Increased usage after the planned handover warning and was always paired with Energy Usage
 **Energy Usage**	**Recommendation**	• **Give higher prominence during the planned handover warning** • **Give moderate prominence during steady-state**
	Justification from results	• Key information for electric vehicles [82] • Decreased significantly with moderate overall fixations • Increased usage after the planned handover warning and was always paired with Battery
 **Hazard Scanner**	**Recommendation**	• **Give lower prominence after handover events to manual driving, consistent after warnings** • **Give higher prominence during steady-state**
	Justification from results	• Developed from multiple studies [4], [71] • No significant change in fixations with high overall fixations • Lower usage after both handover events to manual driving
 **Navigation**	**Recommendation**	• **Give lower prominence after handover events and familiar routes** • **Give higher prominence during steady-state in new routes**
	Justification from results	• Familiar information in vehicles today • No significant change with high overall fixations • Lower usage after handover events
 **Road Signs**	**Recommendation**	• **Give lower prominence immediately after emergency handover** • **Give moderate prominence during steady-state**
	Justification from results	• Developed from multiple studies [4], [71] • Decreased significantly with high overall fixations • Consistent usage after planned handover, but decreased after emergency handover
Traffic Conditions	**Recommendation**	• **Give lower prominence after handover events, consistent after warnings** • **Give lower prominence during steady-state**
	Justification from results	• Familiar information in vehicles today • No significant change with low overall fixations • Lower usage after handover events to manual driving
 **Vehicle Warnings**	**Recommendation**	• **Give higher prominence after events** • **Give lower prominence during steady-state**
	Justification from results	• No significant change with low overall fixations • Higher usage after emergency handover and both warning events • Consistent after planned handover

occur, participants continue to use this type of detailed system transparency information. After all handover events, usage of the Hazard Scanner significantly decreased, suggesting its utility is only applicable to partially automated driving. With this being considered, the implications of future interface design are challenging. It is evident by the consistent usage, ththe Hazard Scanner provides important system transparency information to drivers, enabling confirmation of the vehicle's intended actions. However, with previous studies suggesting declining usage after prolonged steady state driving, future designers of partially automated interfaces will need to consider how this information can be presented to maintain its usage by drivers.

Both Road Signs and the Automated Driving indicator fell significantly in usage over the course of the trial week suggesting that participants began to rely on other information types to confirm both the system transparency and technical competence of the vehicle.

E. Design Recommendations

Table VIII details a summary of all the fixation results. It synthesises the steady state results alongside the changes in fixations after each of the handover and warning events to form preliminary recommendations as to how information could be adapted on a future adaptive interface.

F. Strengths and Limitations

The HMI recommendations developed through this study's unique longitudinal study design are the first important step in defining how an adaptive interface could be designed. Evidently, there is now a need to understand the safety implications of the recommendations. For example, the presentation of Action Explanation (what and why information) may have consequences for driver distraction in emergency situations. Hence, future studies can now look to build on the novel findings presented in this paper to continue to refine and develop the guidelines for adaptive interfaces.

In addition to the HMI recommendations presented in this paper, the longitudinal study design helped to mitigate any visual salience imbalances of the information icons and novelty effects of a participants first time inside a driving simulator. The significant changes in the usage of information presented to drivers is an indication of the advantage of the methodology over studies using a single-exposure design. Genders were represented approximately equally in the study, though a more diverse range of age demographics should be aimed for in future studies. The sample size of 27 means while more work is required to generalise the results to the wider driving population, they can be considered transferrable in for future simulator studies, as the field of adaptive interfaces continues to be developed.

As is the case for all studies utilising eye tracking, the 'eye-mind' connection was assumed. This assumes that the information fixated on by the participant, is actively being cognitively processed [75]. While a person's cognitive processing of an information icon can still be ongoing after the fixation has moved [76], [77], the majority of the information is acquired visually by drivers [78], [79]; hence the assumption has been considered valid and used previously in simulated driving studies [80], [81].

Also considering the demographics of the participants who took part, the majority were below between 18-34 years old. Future studies should consider a stronger representation of age ranges to understand any age related effects on glance fixation behaviour.

V. Conclusion

This study aimed to define the glance behaviour for drivers of partially automated vehicles across both steady state and driving event simulations, to inform the design of an adaptive interface. By synthesising the range of results gathered from the eye tracking data, guidelines for the design of future adaptive interfaces to support the use of future partially automated vehicles can be provided. However, future research will need to consider the creation of a prototype interface based on the design recommendations, to test for driver performance, safety and acceptance.

This paper contributes the first step to designing these future adaptive interfaces and is one of the first to explore the change in glance fixation behaviour, using eye tracking, in a partially automated vehicle to inform the design of future adaptive interfaces. This study has found:

- The importance of Action Explanation; a textual description of the current state of the vehicle and why actions were being taken. This information was consistently used across the longitudinal steady state automated driving and increased significantly in usage after most of the driving events.
- How certain information types' usage increased in tandem in response to the varying driving conditions. Action Explanation increased in usage alongside Vehicle Warnings; the Battery icon always changed in usage alongside Energy Usage. The study suggests that an interface should provide drivers with an explanation as to what the vehicle is doing, as well as why. It was notable to observe how increases in usage towards detailed information was also accompanied by increases to more visual, relatively simpler representations- indicating the importance of presenting both on an HMI for a partially automated vehicle (or, in the case of the Battery and Energy Usage, in current electric vehicles today)
- Different information types could be adapted to a higher or lower prominence accordingly, during continuous, steady state automated driving and after driving events. Given the risk of exposing the driver to cognitive overload with the range of information that interfaces in automated vehicles today present, the opportunity to automatically adapt the information presented based on the results of this study may reduce this risk.

Methodologically, the significant changes observed in the glance fixation behaviour suggest that single exposure HMI evaluations may be limited in their assessment. This study's three day design was sufficient to capture the significant changes in fixations, given that there was no significant change in fixations after day 2. Future studies should consider using a similar study design when conducting human factors studies with partially automated vehicles (and higher). Secondly, the shortlist of nine information types derived for use in this study provides a methodologically derived shortlist of information that can be considered representative of future partially automated vehicle interfaces. Finally, the glance fixation behaviour characterised can contribute to the design of future interfaces that are capable of adapting the information presented to the driver, creating a more usable interface that may avoid the challenges of cognitive overload.

References

[1] B. Reimer, "Driver assistance systems and the transition to automated vehicles: A path to increase older adult safety and mobility?," *Public Policy Aging Rep.*, vol. 24, no. 1, pp. 27–31, Jan. 2014.

[2] Canalys, "10 % of new cars in the US sold with level 2 autonomy features," 2019.

[3] SAE, "Taxonomy and definitions for terms related to on-road motor vehicle automated driving systems (J3016_201806)," *SAE Int.*, Jun. 2018.

[4] A. Ulahannan *et al.*, "User expectations of partial driving automation capabilities and their effect on information design preferences in the vehicle," *Appl. Ergon.*, vol. 82, p. 102969, 2020, doi: https://doi.org/10.1016/j.apergo.2019.102969.

[5] Y. Forster, S. Hergeth, F. Naujoks, J. F. Krems, and A. Keinath, "What and how to tell beforehand: The effect of user education on understanding, interaction and satisfaction with driving automation," *Transp. Res. Part F Traffic Psychol. Behav.*, vol. 68, pp. 316–335, 2020, doi: https://doi.org/10.1016/j.trf.2019.11.017.

[6] S. M. Casner and E. L. Hutchins, "What Do We Tell the Drivers? Toward Minimum Driver Training Standards for Partially Automated Cars," *J. Cogn. Eng. Decis. Mak.*, vol. 13, no. 2, pp. 55–66, 2019, doi: 10.1177/1555343419830901.

[7] K. Blömacher, G. Nöcker, and M. Huff, "The role of system description for conditionally automated vehicles," *Transp. Res. Part F Traffic Psychol. Behav.*, vol. 54, pp. 159–170, Jan. 2018, doi: 10.1016/j.trf.2018.01.010.

[8] V. A. Banks, K. L. Plant, and N. A. Stanton, "Driver error or designer error: Using the Perceptual Cycle Model to explore the circumstances surrounding the fatal Tesla crash on 7th May 2016," *Saf. Sci.*, vol. 108, pp. 278–285, Oct. 2018, doi: 10.1016/j.ssci.2017.12.023.

[9] P. Olsen, "Cadillac Tops Tesla in Consumer Reports' First Ranking of Automated Driving Systems," *Consum. Rep.*, Oct. 2018.

[10] N. Lyu, Z. Duan, L. Xie, and C. Wu, "Driving experience on the effectiveness of advanced driving assistant systems," in *2017 4th International Conference on Transportation Information and Safety, ICTIS 2017 - Proceedings*, 2017, pp. 987–992, doi: 10.1109/ICTIS.2017.8047889.

[11] U. E. Manawadu, T. Kawano, S. Murata, M. Kamezaki, and S. Sugano, "Estimating driver workload with systematically varying traffic complexity using machine learning: Experimental design," in *Advances in Intelligent Systems and Computing*, 2018, vol. 722, pp. 106–111, doi: 10.1007/978-3-319-73888-8_18.

[12] A. Riener, S. Boll, and A. Kun, "Automotive User Interfaces in the Age of Automation : report of Dagstuhl Seminar 16262," in *Dagstuhl Reports*, 2016, vol. 6, no. 6, pp. 111–159, doi: 10.4230/DagRep.6.6.111.

[13] S. Birrell, M. Young, N. Stanton, and P. Jennings, "Using adaptive interfaces to encourage smart driving and their effect on driver workload," in *Advances in Intelligent Systems and Computing*, vol. 484, no. Chapter 3, Cham: Springer International Publishing, 2017, pp. 31–43.

[14] M. Walch, K. Mühl, J. Kraus, T. Stoll, M. Baumann, and M. Weber, "From Car-Driver-Handovers to Cooperative Interfaces: Visions for Driver–Vehicle Interaction in Automated Driving," *Automot. User Interfaces*, pp. 273–294, Jan. 2017.

[15] W. Stuerzlinger, O. Chapuis, D. Phillips, and N. Roussel, "User interface façades: Towards fully adaptable user interfaces," in *UIST 2006: Proceedings of the 19th Annual ACM Symposium on User Interface Software and Technology*, 2008, pp. 309–318, doi: 10.1145/1166253.1166301.

[16] A. D. Andre and C. D. Wickens, "When Users Want What's not Best for Them," *Ergon. Des. Q. Hum. Factors Appl.*, vol. 3, no. 4, pp. 10–14, 1995, doi: 10.1177/106480469500300403.

[17] R. W. Bailey, "Performance vs. preference," in *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, 1993, vol. 37, no. 4, pp. 282–286.

[18] M. W. Scerbo, "Theoretical perspectives on adaptive automation," *Autom. Hum. Perform. Theory Appl.*, pp. 37–63, 2018, doi: 10.1201/9781315137957.

[19] J. G. Morrison, D. Cohen, and J. P. Gluckman, "Prospective Principles and Guidelines for the Design of Adaptively Automated Crewstations," *Proc. Seventh Int. Symp. Aviat. Psychol.*, pp. 172–177, 1993.

[20] W. Piechulla, C. Mayser, and H. Gehrke, "Reducing driver's mental workload by means of an adaptive man-machine interface," vol. 6, no. 4, pp. 233–248, Dec. 2003.

[21] R. Brostrom, J. Engstrom, A. Agnvall, and G. Markkula, "Towards the next generation intelligent driver information system (IDIS): The Volvo car interaction manager concept," *13th World Congr. Intell. Transp. Syst. Serv.*, p. 32, Jan. 2006.

[22] E. Hollnagel and D. D. Woods, *Joint cognitive systems: Foundations of cognitive systems engineering*. CRC Press, 2005.

[23] P. A. Hancock and M. H. Chignell, "Mental Workload Dynamics in Adaptive Interface Design," *IEEE Trans. Syst. Man Cybern.*, vol. 18, no. 4, pp. 647–658, 1988, doi: 10.1109/21.17382.

[24] I. Neumann, T. Franke, P. Cocron, F. Bühler, and J. F. Krems, "Eco-driving strategies in battery electric vehicle use - How do drivers adapt over time?," *IET Intell. Transp. Syst.*, vol. 9, no. 7, pp. 746–753, 2015, doi: 10.1049/iet-its.2014.0221.

[25] J. Hussain *et al.*, "Model-based adaptive user interface based on context and user experience evaluation," *J. Multimodal User Interfaces*, vol. 12, no. 1, pp. 1–16, 2018, doi: 10.1007/s12193-018-0258-2.

[26] N. Sarter, "Coping with complexity through adaptive interface design," in *International Conference on Human-Computer Interaction*, 2007, pp. 493–498.

[27] S. Khastgir, S. Birrell, G. Dhadyalla, and P. Jennings, "Calibrating trust to increase the use of automated systems in a vehicle," in *Advances in Intelligent Systems and Computing*, vol. 484, no. Chapter 45, Cham: Springer, Cham, 2017, pp. 535–546.

[28] S. Kujala, R. Mugge, and T. Miron-Shatz, "The role of expectations in service evaluation: A longitudinal study of a proximity mobile payment service," *Int. J. Hum. Comput. Stud.*, vol. 98, pp. 51–61, 2017, doi: 10.1016/j.ijhcs.2016.09.011.

[29] A. Ulahannan, P. Jennings, L. Oliveira, and S. Birrell, "Designing an Adaptive Interface: Using Eye Tracking to Classify How Information Usage Changes Over Time in Partially Automated Vehicles," *IEEE Access*, vol. 8, pp. 16865–16875, 2020, doi: 10.1109/ACCESS.2020.2966928.

[30] Y. Liang, W. Wang, J. Qu, and J. Yang, "Comparison Study of Visual Search on 6 Different Types of Icons," in *Journal of Physics: Conference Series*, 2018, vol. 1060, no. 1, p. 12031, doi: 10.1088/1742-6596/1060/1/012031.

[31] T. Lindberg and R. Näsänen, "The effect of icon spacing and size on the speed of icon processing in the human visual system," *Displays*, vol. 24, no. 3, pp. 111–120, 2003, doi: 10.1016/S0141-9382(03)00035-0.

[32] M. Rigou, S. Sirmakessis, R. Ventura, A. Fernández, C. P. Antonopoulos, and N. Voros, "Designing user interfaces for the elderly," in *RADIO--Robots in Assisted Living: Unobtrusive, Efficient, Reliable and Modular Solutions for Independent Ageing*, Springer, 2018, pp. 113–148.

[33] K. Krafka *et al.*, "Eye Tracking for Everyone," in *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, 2016, vol. 2016-Decem, pp. 2176–2184, doi: 10.1109/CVPR.2016.239.

[34] A. Papoutsaki, N. Daskalova, P. Sangkloy, J. Huang, J. Laskey, and J. Hays, "WebGazer: Scalable webcam eye tracking using user interactions," *IJCAI Int. Jt. Conf. Artif. Intell.*, vol. 2016-Janua, pp.

3839–3845, Jan. 2016.
[35] A. T. Duchowski, "Eye Tracking Methodology," *Eye Track. Methodol.*, vol. 328, p. 614, Jan. 2017, doi: 10.1007/978-3-319-57883-5.
[36] D. R. Large, G. Burnett, E. Crundall, G. Lawson, and L. Skrypchuk, "Twist it, touch it, push it, swipe it: Evaluating secondary input devices for use with an automotive touchscreen HMI," *AutomotiveUI 2016 - 8th Int. Conf. Automot. User Interfaces Interact. Veh. Appl. Proc.*, pp. 161–168, Jan. 2016, doi: 10.1145/3003715.3005459.
[37] B. Mehler, D. Kidd, B. Reimer, I. Reagan, J. Dobres, and A. McCartt, "Multi-modal assessment of on-road demand of voice and manual phone calling and voice navigation entry across two embedded vehicle systems," *Ergonomics*, vol. 59, no. 3, pp. 344–367, Oct. 2016, doi: 10.1080/00140139.2015.1081412.
[38] F. Vicente, Z. Huang, X. Xiong, F. De La Torre, W. Zhang, and D. Levi, "Driver Gaze Tracking and Eyes off the Road Detection System," *IEEE Trans. Intell. Transp. Syst.*, vol. 16, no. 4, pp. 2014–2027, Jan. 2015, doi: 10.1109/TITS.2015.2396031.
[39] R. A. Young, "Evaluation of the total eyes-off-road time glance criterion in the NHTSA visual-manual guidelines," *Transp. Res. Rec.*, vol. 2602, no. 1, pp. 1–9, Jan. 2016, doi: 10.3141/2602-01.
[40] S. A. Birrell and M. Fowkes, "Glance behaviours when using an in-vehicle smart driving aid: A real-world, on-road driving study," *Transp. Res. Part F Traffic Psychol. Behav.*, vol. 22, no. C, pp. 113–125, Jan. 2014, doi: 10.1016/j.trf.2013.11.003.
[41] Y. Peng and L. N. Boyle, "Driver's adaptive glance behavior to in-vehicle information systems," *Accid. Anal. Prev.*, vol. 85, no. C, pp. 93–101, Dec. 2015, doi: 10.1016/j.aap.2015.08.002.
[42] S. Djamasbi, M. Siegel, J. Skorinko, and T. Tullis, "Online viewing and aesthetic preferences of generation y and the baby boom generation: Testing user web site experience through eye tracking," *Int. J. Electron. Commer.*, vol. 15, no. 4, pp. 121–157, Jan. 2011, doi: 10.2753/JEC1086-4415150404.
[43] C. Ehmke and S. Wilson, "Identifying web usability problems from eye-tracking data," *People Comput. XXI HCI.But Not as We Know It - Proc. HCI 2007 21st Br. HCI Gr. Annu. Conf.*, vol. 1, pp. 119–128, Jan. 2007.
[44] S. Yusuf, H. Kagdi, and J. I. Maletic, "Assessing the comprehension of UML class diagrams via eye tracking," *15th IEEE Int. Conf. Progr. Compr.*, pp. 113–122, Jan. 2007.
[45] M. Resnick and W. Albert, "The Impact of Advertising Location and User Task on the Emergence of Banner Ad Blindness: An Eye-Tracking Study," *Int. J. Hum. Comput. Interact.*, vol. 30, no. 3, pp. 206–219, Jan. 2014, doi: 10.1080/10447318.2013.847762.
[46] T. Blascheck, K. Kurzhals, M. Raschke, M. Burch, D. Weiskopf, and T. Ertl, "Visualization of Eye Tracking Data: A Taxonomy and Survey," *Comput. Graph. Forum*, vol. 36, no. 8, pp. 260–284, Jan. 2017, doi: 10.1111/cgf.13079.
[47] J. L. Orquin and K. Holmqvist, "Threats to the validity of eye-movement research in psychology," *Behav. Res. Methods*, vol. 50, no. 4, pp. 1–12, Jul. 2018, doi: 10.3758/s13428-017-0998-z.
[48] E. . Poulton, "Peripheral vision, refractoriness and eye movements in fast oral reading.," *Br. J. Psychol.*, vol. 53, no. 4, pp. 409–419, Jan. 1962, doi: 10.1111/j.2044-8295.1962.tb00846.x.
[49] E. Cutrell and Z. Guan, "What are you looking for?: An eye-tracking study of information usage in Web search," in *Conference on Human Factors in Computing Systems - Proceedings*, 2007, pp. 407–416, doi: 10.1145/1240624.1240690.
[50] B. R. Manor and E. Gordon, "Defining the temporal threshold for ocular fixation in free-viewing visuocognitive tasks," *J. Neurosci. Methods*, vol. 128, no. 1–2, pp. 85–93, Sep. 2003, doi: 10.1016/S0165-0270(03)00151-1.
[51] T. A. Salthouse and C. L. Ellis, "Determinants of eye-fixation duration," *Am. J. Psychol.*, pp. 207–234, Jan. 1980.
[52] R. Andersson, M. Nyström, and K. Holmqvist, "Sampling frequency and eye-tracking measures: how speed affects durations, latencies, and more," *J. Eye Mov. Res.*, vol. 3, no. 3, pp. 1–12, Jan. 2010, doi: 10.16910/jemr.3.3.6.
[53] BSI, "Road vehicles. Ergonomic aspects of transport information and control systems. Specifications and test procedures for in-vehicle visual presentation," BS EN ISO 15008:2017, 2017.
[54] UNECE, "UN Regulation No. 121 - Rev.2 - Identification of controls, tell-tales and indicators," 121 Amend. 7, 2018.
[55] J. Rasmussen, "Skills, Rules, and Knowledge; Signals, Signs, and Symbols, and Other Distinctions in Human Performance Models," *IEEE Trans. Syst. Man Cybern.*, vol. SMC-13, no. 3, pp. 257–266, Jan. 1983, doi: 10.1109/TSMC.1983.6313160.
[56] M. Tönnis, V. Broy, and G. Klinker, "A survey of challenges related to the design of 3D user interfaces for car Drivers," in *Proceedings - IEEE Virtual Reality*, 2006, vol. 2006, p. 134, doi: 10.1109/VR.2006.19.
[57] J. K. Choi and Y. G. Ji, "Investigating the Importance of Trust on Adopting an Autonomous Vehicle," *Int. J. Hum. Comput. Interact.*, vol. 31, no. 10, pp. 692–702, Jul. 2015, doi: 10.1080/10447318.2015.1070549.
[58] S. I. Becker, A. M. Harris, D. Venini, and J. D. Retell, "Visual search for color and shape: When is the gaze guided by feature relationships, when by feature values?," *J. Exp. Psychol. Hum. Percept. Perform.*, vol. 40, no. 1, pp. 264–291, Jan. 2014.
[59] C. Barras and D. Kerzel, "Salient-but-irrelevant stimuli cause attentional capture in difficult, but attentional suppression in easy visual search," *Psychophysiology*, vol. 54, no. 12, pp. 1826–1838, Jan. 2017, doi: 10.1111/psyp.12962.
[60] S. Ocklenburg, "Tachistoscopic viewing and dichotic listening," *Lateralized Brain Funct.*, pp. 3–28, Jan. 2017.
[61] J. Koo, J. Kwac, W. Ju, M. Steinert, L. Leifer, and C. Nass, "Why did my car just do that? Explaining semi-autonomous driving actions to improve driver understanding, trust, and performance," *Int. J. Interact. Des. Manuf.*, vol. 9, no. 4, pp. 269–275, Apr. 2015, doi: 10.1007/s12008-014-0227-2.
[62] Tobii, "Understanding Pro Lab's eye tracking metrics," *Tobii Technology*, 2021. [Online]. Available: https://www.tobiipro.com/learn-and-support/learn/steps-in-an-eye-tracking-study/data/understanding-Pro-Labs-eye-tracking-metrics/. [Accessed: 15-Apr-2021].
[63] D. Hu, X. Feng, X. Zhao, H. Li, J. Ma, and Q. Fu, "Impact of HMI on driver's distraction on a freeway under heavy foggy condition based on visual characteristics," *J. Transp. Saf. Secur.*, pp. 1–24, 2020, doi: 10.1080/19439962.2020.1853641.
[64] Department for Transport, "Commuting trends in England," 2015.
[65] A. Olsen, "The Tobii I-VT Fixation Filter: Algorithm description," *Tobii Technol.*, p. 21, 2012.
[66] M. Costa, A. Simone, V. Vignali, C. Lantieri, and N. Palena, "Fixation distance and fixation duration to vertical road signs," *Appl. Ergon.*, vol. 69, pp. 48–57, 2018, doi: 10.1016/j.apergo.2017.12.017.
[67] N. Müller, S. Baumeister, I. Dziobek, T. Banaschewski, and L. Poustka, "Validation of the Movie for the Assessment of Social Cognition in Adolescents with ASD: Fixation Duration and Pupil Dilation as Predictors of Performance," *J. Autism Dev. Disord.*, vol. 46, no. 9, pp. 2831–2844, Sep. 2016, doi: 10.1007/s10803-016-2828-z.
[68] G. Weinberg, B. Harsham, and Z. Medenica, "Evaluating the usability of a head-up display for selection from choice lists in cars," *Proc. 3rd Int. Conf. Automot. User Interfaces Interact. Veh. Appl. AutomotiveUI 2011*, pp. 39–46, 2011, doi: 10.1145/2381416.2381423.
[69] N. J. Starkey, S. G. Charlton, N. Malhotra, and E. Lehtonen, "Drivers' response to speed warnings provided by a smart phone apps," *Transp. Res. Part C Emerg. Technol.*, vol. 110, pp. 209–221, 2020, doi: 10.1016/j.trc.2019.11.020.
[70] M. Beggiato, F. Hartwich, K. Schleinitz, J. Krems, I. Othersen, and I. Petermann-Stock, "What would drivers like to know during automated driving? Information needs at different levels of automation.," in *7th conference on driver assistance*, 2015.
[71] A. Ulahannan *et al.*, "Using the ideas café to explore trust in autonomous vehicles," in *Advances in Intelligent Systems and Computing*, 2019, vol. 796, pp. 3–14, doi: 10.1007/978-3-319-93888-2_1.
[72] M. Körber, L. Prasch, and K. Bengler, "Why Do I Have to Drive Now? Post Hoc Explanations of Takeover Requests," *Hum. Factors*, vol. 60, no. 3, pp. 305–323, Jan. 2018, doi: 10.1177/0018720817747730.
[73] T. Jung, C. Kaß, D. Zapf, and H. Hecht, "Effectiveness and user acceptance of infotainment-lockouts: A driving simulator study," *Transp. Res. Part F Traffic Psychol. Behav.*, vol. 60, pp. 643–656, Jan. 2019.
[74] S. A. Birrell, A. McGordon, and P. A. Jennings, "Defining the accuracy of real-world range estimations of an electric vehicle," in

17th IEEE International Conference on Intelligent Transportation Systems, ITSC 2014, 2014, pp. 2590–2595, doi: 10.1109/ITSC.2014.6958105.
[75] D. E. Kieras and M. A. Just, "New methods in reading comprehension research," *New Methods Read. Compr. Res.*, vol. 70, no. 3, pp. 1–398, Jan. 2018, doi: 10.4324/9780429505379.
[76] G. Underwood and J. Everatt, "The role of eye movements in reading: Some limitations of the eye-mind assumption," *Adv. Psychol.*, vol. 88, no. C, pp. 111–169, Jan. 1992, doi: 10.1016/S0166-4115(08)61744-6.
[77] J. R. Anderson, D. Bothell, and S. Douglass, "Eye Movements Do Not Reflect Retrieval Processes: Limits of the Eye-Mind Hypothesis," *Psychol. Sci.*, vol. 15, no. 4, pp. 225–231, Apr. 2004, doi: 10.1111/j.0956-7976.2004.00656.x.
[78] M. Sivak, "The information that drivers use: Is it indeed 90% visual?," *Perception*, vol. 25, no. 9, pp. 1081–1089, Jan. 1996, doi: 10.1068/p251081.
[79] D. Shinar, "Looks are (almost) everything: Where drivers look to get information," *Hum. Factors*, vol. 50, no. 3, pp. 380–384, Jan. 2008, doi: 10.1518/001872008X250647.
[80] T. W. Victor, J. L. Harbluk, and J. A. Engström, "Sensitivity of eye-movement measures to in-vehicle task difficulty," *Transp. Res. Part F Traffic Psychol. Behav.*, vol. 8, no. 2 SPEC. ISS., pp. 167–190, Jan. 2005, doi: 10.1016/j.trf.2005.04.014.
[81] Y. Liang, M. L. Reyes, and J. D. Lee, "Real-time detection of driver cognitive distraction using support vector machines," *IEEE Trans. Intell. Transp. Syst.*, vol. 8, no. 2, pp. 340–350, Jan. 2007, doi: 10.1109/TITS.2007.895298.
[82] E. Graham-Rowe *et al.*, "Mainstream consumers driving plug-in battery-electric and plug-in hybrid electric cars: A qualitative analysis of responses and evaluations," *Transp. Res. Part A Policy Pract.*, vol. 46, no. 1, pp. 140–153, 2012, doi: 10.1016/j.tra.2011.09.008.

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