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Designing an Adaptive Interface: Using Eye Tracking to Classify How Information Usage Changes Over Time in Partially Automated Vehicles

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ABSTRACT While partially automated vehicles can provide a range of benefits, they also bring about new Human Machine Interface (HMI) challenges around ensuring the driver remains alert and is able to take control of the vehicle when required. While humans are poor monitors of automated processes, specifically during 'steady state' operation, presenting the appropriate information to the driver can help. But to date, interfaces of partially automated vehicles have shown evidence of causing cognitive overload. Adaptive HMIs that automatically change the information presented (for example, based on workload, time or physiologically), have been previously proposed as a solution, but little is known about how information should adapt during steady-state driving. This study aimed to classify information usage based on driver experience to inform the design of a future adaptive HMI in partially automated vehicles. The unique feature of this study over existing literature is that each participant attended for five consecutive days; enabling a first look at how information usage changes with increasing familiarity and providing a methodological contribution to future HMI user trial study design. Seventeen participants experienced a steady-state automated driving simulation for twenty-six minutes per day in a driving simulator, replicating a regularly driven route, such as a work commute. Nine information icons, representative of future partially automated vehicle HMIs, were displayed on a tablet and eye tracking was used to record the information that the participants fixated on. The results found that information usage did change with increased exposure, with significant differences in what information participants looked at between the first and last trial days. With increasing experience, participants tended to view information as confirming technical competence rather than the future state of the vehicle. On this basis, interface design recommendations are made, particularly around the design of adaptive interfaces for future partially automated vehicles.

INDEX TERMS Intelligent vehicles, autonomous vehicles, interface, eye tracking, information requirements, HMI.

I. INTRODUCTION

Partially automated vehicles (SAE Level 2-3) have the potential to provide a wide range of benefits for users, such as increased safety and a better user experience compared to current vehicles [1]. However, they also introduce new challenges for the Human Machine Interface (HMI) in the vehicle, namely around ensuring the driver remains in-the-loop and ready to take over control from the system when notified [2]. It is well understood that humans are inefficient at monitoring an automated process [3]–[6] and this can have challenging implications for future vehicles that fail to support the driver during the handover process [7]. For example, mode confusion is one such challenge; where the user misunderstands whether it is the system or the user who is in control of the vehicle. This effect has been long observed in other contexts, such as in the marine industry [7] and has been shown to increase the risk of accidents.

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This poor efficiency when monitoring an automated process has been attributed to an increase in the cognitive complexity of using the vehicle for the user, as the driver is required to understand the vehicle's intention, predict future actions and continuously make judgements as to whether an intervention is required [8], [9]. Designing HMIs that are able to communicate effectively with the driver can be a positive influence on driver's use of an automated vehicle [10], [11], by enabling drivers to develop accurate mental models of the vehicle's intended actions [12]. However, there is some preliminary evidence to suggest that interfaces in partially automated vehicles today are not effective. For example, in a preliminary analysis of a fatal Tesla Autopilot crash in 2016, there was evidence to suggest that there was a greater implication on the poor design of the system's interface, rather than driver error, that led to the fatality [8].

Currently, a variety of information is presented to the driver in the hope that some of the information will be useful and keep the driver informed and in-the-loop [13]. However, as a result, too much information is presented which increases the complexity of the interaction between the driver and the vehicle [14]–[17]. This often results in either the driver mistaking the intentions and capabilities of the vehicle or falling out of the loop and disengaging with the monitoring task, thereby reducing the ability to respond to emergency events [18]–[20].

This issue of drivers disengaging with the monitoring task is problematic as it is likely that the majority of a driver's time in an automated vehicle will be uneventful and consist of non-emergency scenarios. According to the World Health Organization, road traffic accidents in the UK averaged less than 3 per 100,000 people [21]. If a similar rate is assumed for partially automated vehicles, it is a justifiable assumption that most of the time inside a partially automated vehicle will be spent in non-emergency scenarios. Drivers will be asked to monitor these partially automated systems for periods of time which are likely to be uneventful and monotonous – increasing the risk of a driver failing to monitor the vehicle appropriately, as a result of boredom [22]. Further, the likely benefits of an automated system are typically only realized in non-critical conditions [4], [7], so it is important to the design of future HMI that these steady-state scenarios are carefully considered. Most notably, to date, there is a dearth of literature considering how HMIs for partially automated vehicles should consider these monotonous, steady-state portions of driving.

To better design an HMI that can appropriately support drivers and realize the benefits of using partially automated systems, driver information usage – particularly during steady-state driving – must be understood. To date, there is little research in this area, with the majority of previous research being more focused on the occasional (though still important) emergency handover from automation, as for example the studies by [18]–[20].

A. ADAPTIVE INTERFACES AS A SOLUTION

Adaptive interfaces in partially automated vehicles have been suggested as a solution to ensuring drivers remain in the loop and engaged with monitoring the automated system [23]. Preliminary studies have supported the idea as a solution to managing the information presented to the driver (or operator) so as to avoid issues of cognitive overload and distraction [24]–[26].

An adaptive interface is able to automatically change the information presented to the driver to provide the appropriate information at the right time, rather than display all information in a fixed display [27]. This is in contrast to an adaptable interface, which allows the user to define what information they wish to be presented with. There are factors to consider with each approach. An adaptable interface is relatively simpler, by giving control to the user, there is a lower risk of confusion by the system presenting the wrong or inappropriate information [27]. However, there is evidence to suggest the user may not be the best judge of the information they require to achieve optimal performance with a system in general [28], [29].

In contrast, the adaptive interface is able to select the information required automatically; however, the main challenges remain around what drives the adaption of the information [30]. Initial concepts have used a variety of measures to drive adaption, such as driver performance and driver modelling [31], workload [17], [32] and physiological measures [31], [33]. There is also an increasing body of work on identifying the driver's intentions when inside a vehicle, using a series of different sensor-based measures. Preliminary results have been promising for driver behaviour identification [34], and consequently as a driver of information adaption.

One aspect that has been largely overlooked (which may be able to connect these different approaches) is the temporal effect of the driver's developing experience with the system as they continue to use it [27], [35]. This temporal effect has been generally recognised as an important factor in understanding how a user interacts with a system or product. For example, it has been found that drivers of electric vehicles develop significantly more strategies for eco-driving over time as they become more familiar with the nuances of the system [36]. In the development of trust in vehicles, there is a strong consensus that this is a dynamic process that changes over time as familiarity with the system increases [37]. How users evaluate the usability and experience of a service is also driven by temporal effects [38].

There are numerous challenges for HMIs in supporting the driver in safely using a partially automated vehicle. Particularly, there has been a lack of understanding as to what information should be presented to help support drivers during monotonous steady-state driving. Furthermore, it is evident that the longitudinal effects of increasing familiarity with a partially automated vehicle on information usage are yet to be studied. Hence, with adaptive interfaces being touted as a solution to this HMI challenge, the opportunity was identified to investigate information usage for partially automated vehicles; classify how information usage changes with increasing familiarity and to begin to define an agent of adaption for an adaptive interface.

B. AIM

The aim of this study is to classify the information usage for drivers of partially automated vehicles and understand how these requirements change over time with increased exposure to the system during steady-state driving. This will begin to inform the design of an adaptive interface.

C. OBJECTIVES

During one week of partially automated vehicle simulations, this study addressed the aim by:

- Measuring the overall percentage of time that participants fixated on the information display as a whole.
- Measuring the overall number of fixations to specific information icons.
- Identifying key trends in how information usage changed with increased exposure to the system.

II. METHOD

A. STUDY DESIGN

The study used a longitudinal five-day within-subjects design. Participants experienced a 13 minute partially automated driving simulation twice per day. During each simulation, participants were presented with nine information icons on an iPad and wore eye-tracking glasses. The number of fixations to each information icon on the display was recorded.

B. PARTICIPANTS

For this study, 20 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 were paid £5 per session attended and an additional £5 for completing all sessions. This meant a participant who completed all five sessions was paid £30 in total.

Three participants were unable to complete the full trial week because of scheduling conflicts. These participants were omitted from the results. Detailed demographics of the participants who completed the study can be seen below in Table 1.

TABLE 1. Breakdown of participant demographics.

Information	Participants with complete data
Gender	8 (Male), 9 (Female)
Age	2 (18-24), 11 (25-34), 1 (66-64), 3 (65 or older)
Nationality	UK (10), Italy (2), Germany (1), Netherlands (1), Ireland (1), Nigeria (1), Sri Lanka (1) Syria (1)
Driving Experience	1 (< 1 year), 3 (3-5 years), 13 (More than 5 years)
Miles per Year	3 (0-4000), 7 (4000-8000), 7 (8000-12,000)
Driving Days per Week	2 (Once), 3 (2-3), 1 (4-5), 2 (5-6), 8 (Daily)
Highest Education Level	2 (GCSE), 6 (degree), 10 (Masters), 2 (Doctorate)

C. MATERIALS

1) SELECTION OF INFORMATION TO DISPLAY

To understand how information usage changes, there first needed to be a shortlist of information to present to participants.

Numerous standards were consulted, such as BS EN ISO 15008:2017 [39] and ECE 121 [40], that also include definitions of the minimum information requirements for vehicles today. Information such as vehicle speed was omitted from this study because it is currently a mandatory requirement in vehicles today and could not be adapted. Other non-legally required information was shortlisted with close collaboration with the industrial partner in the project. Furthermore, existing interfaces from Tesla and Cadillac [13] for partial driving automation were reviewed and information added to the shortlist. Through a series of workshops with academic and industrial experts, the number of information eligible for the study was reduced to 30 pieces of information.

However, 30 pieces of information would have been impractical to present throughout the study. To narrow down the selection of information to a more practical number, the information was reviewed against three models: Skills, Rules, Knowledge (SRK) [41]; Primary, Secondary, Tertiary (PST) [42] and the Trust model by Choi and Ji (TM) [10]. There were two key reasons for categorising against three models. First, this ensured that the information presented in the study could be considered representative of a future partially automated vehicle. Second, each model had limitations in its application to information selection, hence using three helped address the limitations of each. The shortlist of 30 pieces of information was categorised into these three models through collaboration with academic and industry professionals.

SRK provided a useful guide to balance the spread of information according to cognitive load. A limitation of this model was that different drivers could ascribe different levels of cognitive load to the information [43]–[45], making accurate placement of information into the three discrete categories of the model difficult. For the SRK model, information that was considered low cognitive demand was classed as Skill (Sk). Information that required the driver to interpret then follow an action was considered Rule (Ru). Finally, information that required the driver to develop a mental model of the information to then draw comparisons to the environment was considered Knowledge (Kno).

The information was also categorised against the PST model [42]. This categorised information based on its role

Mon	Tue	Wed	Thur	Fri
Trial Brief	Sim 1	Sim 1	Sim 1	Sim 1
Sim 1	Sim 2	Sim 2	Sim 2	Sim 2

FIGURE 1. Study Design. Where Sim 1 and 2 are the two 13 minute partially automated driving simulations.

in the driving task. However, as 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. Information that was related to the primary control of the vehicle was classed as Primary (P). Information related to increasing the safety of the vehicle was Secondary (S). Finally, information that was concerned with non-critical information systems was classed as Tertiary (T).

The TM [10] categorised information based on whether the information described the future (System Transparency) or current state (Technical Competence) 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.

Of the 30 pieces of information, nine could be categorised into all three models. Table 2 shows the final categorisations of information along with a brief definition of each. The final interface presented to participants is shown in Figure 2 in the following section.

2) INTERFACE DESIGN

Icons for the nine information icons were designed using Sketch for Mac (version 52.6). These were exported as.png files and brought into Hype 3 for Mac in order to be animated as a vehicle interface.

Visual salience has been found to be more dependent on the relative similarities or dissimilarities of the icons and the ease with which the required information can be found, rather than any specific attribute values [46], [47]. For example, a bolder colour may not necessarily be a more salient icon if other icons are similarly designed.

The researchers tested the prototype interface using tachistoscopic presentation [48] to test the visual salience of the information icons. This was run as 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 (Figure 2) was repeatedly flashed to testers for a period of 200ms with varying positions of icons. Fixations to the information icons were measured using eye-tracking glasses. Consequently, the Hazard Sensor was redesigned from using a photorealistic vehicle to a generic red triangle. Moreover, animation frequencies were made consistent across all icons. Any remaining visual salience imbalances were expected to be mitigated by the unique 5-day longitudinal design of the study.

TABLE 2. Information for study interface (from collaboration with academic and industry professionals). Where Sk = Skills, Ru = Rules, Kno = Knowledge; P = Primary, S = Secondary, T = Tertiary; TC = Technical competence and ST = System Transparency.

Information	Icon	Description	Category
Action Explanation		Described the vehicle's actions in a descriptive statement	Ru/P/TC
Auto Indicator	AUTO	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	50	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 last read road sign. Allowed the driver to confirm the vehicle's sensing capabilities	Ru/S/ST
Traffic	Clear	Presented the current road traffic level	Sk/T/ST
Vehicle Warnings		Would indicate when any issues with the vehicle or hazards in the roadway were detected	Kno/S/TC

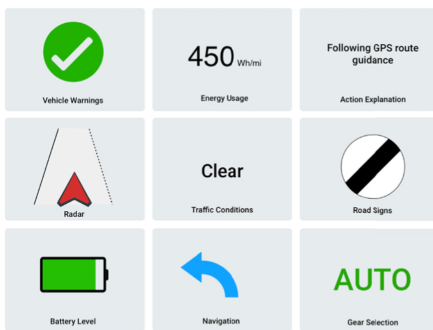

FIGURE 2. Final Interface presented to participants. icons were randomized according to a Latin Squares arrangement for each simulation.

Table 2 below shows the information alongside its final icon representation and how each was categorised according to the three models. Table 3 illustrates a selection of the varying states for each of the information icons.

Figure 2 below depicts how the icons were arranged for one of the simulation sessions.

Information icons were randomized, and the interface was designed to update in real-time, in accordance with the simulated conditions, e.g. the Hazard Scanner was intended to show the curvature of the road and vehicles as they moved into range.

TABLE 3. **The different information states for the information icons. Some remained consistent and some fluctuated. These are indicated accordingly.**

Information	Information Icon States
Action Explanation	Pedestrian detected, slowing down vehicle / Action Explanation; Traffic detected, slowing down / Action Explanation; Moving to middle lane to overtake slower vehicle / Action Explanation; Slower vehicle detected, moving to overtake / Action Explanation
Auto Indicator	AUTO / Automated Indicator No change in the icon as vehicle remained automated
Battery	Battery Level Steadily decreased accordingly
Energy Usage	310 Wh/mi / Energy Usage Fluctuated in response to the acceleration of the vehicle
Hazard Scanner	Hazard Scanner; Hazards; Hazards
Navigation	Navigation; Navigation
Road Signs	Road Signs; 30 / Road Signs; Road Signs
Traffic	Traffic Conditions; Traffic Conditions
Vehicle Warnings	! / Vehicle Warnings; Vehicle Warnings

3) APPARATUS

The nine information icons tested during this research were delivered to participants using an iPad Pro 2018 featuring a 10.5-inch display with a resolution of 2224 by 1668 pixels. This was used as a surrogate for the vehicle's dashboard display. SMI eye-tracking glasses (30 Hz recording) were used to record participant fixations to each of the nine information icons on the iPad display. Glasses provided participants with the freedom of movement that was not possible with mounted eye-tracking setups.

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 3 below.

The driving scenario focused on steady-state driving. Each 13-minute scenario started in a residential area, moving to a dual carriageway, motorway, then finishing on a high-speed rural road. The intention was to replicate the likely typical use case of a partially automated system on a regular route that is familiar to the driver.

FIGURE 3. **WMG 3xD Development Simulator (with iPad positioned as surrogate dashboard display).**

Three potential conflict scenarios were implemented (a pedestrian crossing the road in the distance, a motorway overtake, and a single carriageway overtake), but these did not require driver intervention and were intended to make the driving scenario more realistic.

For every day during the trial week, the simulation followed the same road layout, but there were variances in traffic conditions and vehicles to prevent any learning effects. The goal was to replicate the familiar, steady-state route that a participant would take on a daily commute to a regular location (such as work).

D. PROCEDURE

Participants were invited into the simulator room and informed consent was received. Participants were asked to observe the vehicle working in automated mode and use the information presented to them in any way that made them feel comfortable inside the vehicle. There was no emergency scenario in the simulation, but participants would not have been aware that this was the case and were told that they should be ready to take over control of the vehicle if required.

SMI Glasses 2.0 was used and calibrated before every session (i.e. calibrated twice per participant, every day). On the first day of the trial week, participants were given a familiarisation scenario to allow them to become accustomed to the visuals and the simulation. There was then time for one simulation. On the remaining four days, two simulations a day were presented (totalling nine simulations by the end of the week).

Between simulations, participants were given a five-minute break and offered refreshments. Eye-tracking calibration was repeated, and the participant then completed the second 13-minute scenario. Finally, a time for the next study 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.

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 limited to a minimum threshold of 200ms in length, as fixations below this figure have been found not to be long enough to assume cognitive processing of the information [49]–[51]

TABLE 4. Percentage of time participants spent looking at information for the entire trial week of nine simulations.

Day	Day 1	Day 2	Day 3	Day 4	Day 5
Proportion of time looking at information display (%)	2.87	2.05	2.22	1.89	1.75

To address the aims of this study, three sets of data were analysed:

- Overall percentage of time participants fixated on the information display as a whole, by summing all fixations to the information display for each participant and averaging this for the participant population.
- Overall fixations to each information icon by summing the fixations to each information icon for each participant and averaging this for the participant population.
- Changes in fixations for each information icon by summing the fixations to each icon for each participant for each day. This was then averaged for the participant population. The difference in means between the beginning and end of the trial week was analysed to understand the trend.

In all cases, data was normal; hence the parametric repeated measures ANOVA was used to test for differences in means.

III. RESULTS

SMI BeGaze software reported a recorded gaze samples percentage of 98%. Indicating the eye tracker was successful in tracking and recording fixations to the display.

A. OVERALL PERCENTAGE OF TIME FIXATING ON THE INFORMATION DISPLAY

Table 4 below shows the average percentage of time each participant spent looking at the information display for each day of the trial week.

The percentage of time participants spent looking at the information displayed on the iPad fell from 2.87% on day 1 to 1.75% on day 5.

A repeated-measures ANOVA with a Greenhouse-Geisser correction reported no significant difference between the percentages for each day of the trial ($F(1.322, 21.144) = 0.534$, $p > 0.05$). This means that there was no change in how long participants fixated on the information interface across the trial week.

B. OVERALL FIXATIONS TO EACH OF THE INFORMATION ICONS

Table 5 below shows the eye-tracking data for the trial week as a whole for each information icon displayed.

Action Explanation had the highest average fixations ($f = 41.6$) by the end of the week, followed by the Hazard Scanner ($f = 40.4$). The Battery had the fewest fixations ($f = 13.0$).

TABLE 5. Summary of eye-tracking data for the entire trial week of nine simulations for each information icon displayed.

Information	Icon	Average no. of fixations for the whole week	Average single fixation duration (s)
Action Explanation		41.6	0.329
Auto Indicator		14.3	0.325
Battery		13.0	0.356
Energy Usage		31.2	0.339
Hazard Scanner		40.4	0.348
Navigation		23.8	0.349
Road Signs		20.2	0.363
Traffic		18.7	0.326
Vehicle Warnings		26.2	0.323

A repeated-measures ANOVA with a Greenhouse-Geisser correction reported a significant difference between the mean total fixations for the information icons ($F(3.053, 48.844) = 4.585$, $p < 0.05$).

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

On average, for all information icons, the single fixation durations ranged between 0.323 and 0.363 seconds long. A repeated-measures ANOVA with a Greenhouse-Geisser correction reported that there was no significant difference between the average single fixation durations for each information icon ($F(3.324, 53.186) = 0.947$, $p > 0.05$). This meant that there was no difference in the length of a participants' individual fixations to each information icon.

C. FIXATION CHANGE TRENDS FOR EACH INFORMATION ICON

Table 6 and Figure 4 below show the fixations to each information icon broken down by each day of the trial week.

A significant effect was reported in terms of information icon fixations according to the trial day ($F(2.915, 46.645) = 3.033$, $p < 0.05$).

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

- Navigation ($f\_day3 = 9.18$ vs. $f\_day5 = 1.82$, $p = 0.003$)

TABLE 6. Average number of fixations to each information per day. Note, Day 1 only had one simulation presented.

Information	Icon	Day 1	Day 2	Day 3	Day 4	Day 5
Action Explanation		13.8	5.47	3.24	7.47	11.7
Auto Indicator	AUTO	1.06	1.35	3.18	2.29	6.41
Battery		3.12	0.12	1.94	4.53	3.29
Energy Usage	50	12.9	6.47	7.41	1.47	2.94
Hazard Scanner		6.94	16.4	11.0	3.12	2.94
Navigation		2.00	2.53	9.18	8.24	1.82
Road Signs		2.82	5.24	6.12	4.53	1.47
Traffic	Clear	5.94	1.35	3.18	4.76	3.47
Vehicle Warnings		12.4	4.94	2.00	3.41	3.53

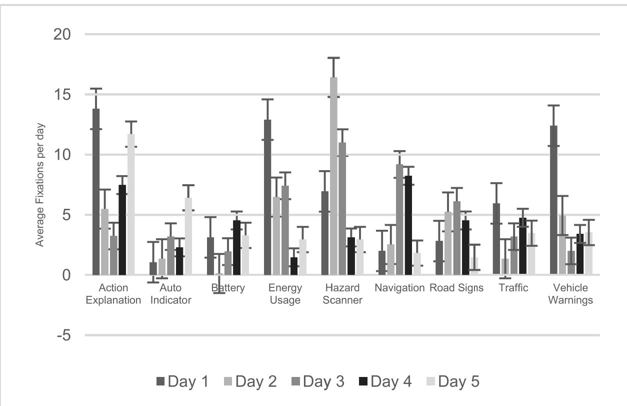

FIGURE 4. Change in total fixations for each information per day. Error bars represent standard error.

- Hazard Scanner (f_$day2 = 16.4$ vs. $f\_day5 = 2.94$, $p = 0.010$)

Some information showed no statistically significant changes overall:

- Vehicle Warnings- between any of the days ($p > 0.05$)
- Energy Usage- between any of the days ($p > 0.05$)
- Road Signs- between any of the days ($p > 0.05$)
- Battery- between any of the days ($p > 0.05$)
- Traffic Conditions displayed a significant drop ($f\_day1 = 5.94$ vs. $f\_day2 = 1.35$, $p = 0.000$) then a significant increase ($f\_day2 = 1.35$ vs. $f\_day4 = 4.76$, $p = 0.037$).

TABLE 7. Summary of key trends in how information usage changed with increased exposure to the system.

Information	Icon	Summary of overall fixation changes
Action Explanation		No significant change overall
Auto Indicator	AUTO	Significant increase overall (f_day1= 1.06 vs. f_day5= 6.41, p= 0.007)
Battery		No significant change overall
Energy Usage	50	No significant change overall
Hazard Scanner		Significant decrease overall (f_$day2$= 16.4 vs. f_day5= 2.94, p= 0.010)
Navigation		Significant decrease overall (f_day3= 9.18 vs. f_day5= 1.82, p= 0.003)
Road Signs		No significant change overall
Traffic	Clear	No significant change overall
Vehicle Warnings		No significant change overall

- Action Explanation displayed a significant drop ($f\_day1 = 13.8$ vs. $f\_day3 = 3.24$, $p = 0.015$), then a significant increase ($f\_day3 = 3.24$ vs. $f\_day5 = 11.7$, $p = 0.002$).

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

The remaining Automated Driving Indicator ($f\_day1 = 1.06$ vs $f\_day5 = 6.41$, $p = 0.007$) showed a significant increase in fixations towards the end of the week. The results of the statistical tests of significance are summarised below in Table 7.

Three models were used to ensure the information presented to participants could be considered representative of future partially automated vehicles. When results were compared against their categorisations, the SRK [41] and PST [42] categories showed no clear trend. However, when information icons and their trends in fixation changes were organised back into the TM [10], it was found that System Transparency information remained the same or reduced significantly in usage. In contrast, Technical Competence information either remained the same or increased in usage. Table 8 below organises the information into their fixation trends and their respective category.

IV. DISCUSSION

This study aimed to classify the information usage for drivers of partially automated vehicles and understand how these requirements change over time with increased exposure to the system, during steady-state driving, to begin to inform the design of an adaptive interface.

TABLE 8. Fixations organised by the TM [10].

Fixation Trend	System Transparency	Technical Competence
Usage increased	None	
Usage remained the same		
Usage reduced		None

The use of a driving simulator allowed safe, repeatable testing of driving scenarios that would not be possible in a real-world environment.

Furthermore, as is true for all studies using eye-tracking, this study made the 'eye-mind' assumption, that the information fixated on by the participant, is actively being cognitively processed [52]. There are limitations to this assumption in that a person's cognitive processing of an information icon can still be ongoing after the fixation has moved [53], [54]. However, driving is an inherently visual task and the majority of a driver's information is acquired visually [55], [56]- consequently, the eye-mind assumption has been used and assumed to be valid in simulator studies before [57], [58].

With regards to the length of time chosen to identify these trends, this is the first experiment of its kind that has deployed a longitudinal experimental design for the investigation of information usage. The significant differences that have been observed in the results is an indication of the strength of this study over the single-exposure studies that currently exist.

While it may be possible that a different trend could be observed if participants are tested over a longer period of time; the objective of the study was to contribute to the fundamental knowledge of how information usage changed with increasing familiarity and the results have shown this accordingly. These results will allow for future studies to continue to build on the study design implemented here.

This section will discuss this aim with reference to the objectives.

A. KEY RESULTS

The overall percentage of time spent fixating on the information display as a whole dropped from 2.87% on day 1 to 1.75% on the final day, but this was not statistically significant.

The Action Explanation ($f = 41.6$) and Hazard Scanner ($f = 40.4$) had significantly more overall fixations than the Battery ($f = 13.0$) ($p = 0.026$ and $p = 0.042$ respectively), but not compared to any other information icon. The length of fixations to each information icon were all statistically similar- indicating that the prototyping of the interface was successful in ensuring all icons were of equal visual salience. Further, these results for average single fixation are in line with previous studies that noted a similar figure [59], validating the design of the information icons and display.

Finally, fixations to information icons did change significantly between the days ($F(2.915, 46.645) = 3.033$, $p < 0.05$). System transparency information either remained the same or reduced significantly in fixations. Technical competence information either remained the same or increased significantly in fixations.

B. IMPLICATIONS FOR ADAPTIVE INTERFACE DESIGN

There are two aspects to the implications of these results for future interface design. The first is that any information that decreased in fixations during steady-state driving is of less importance and should consequently be reduced in prominence. The second aspect is also to recognise that some information is important to the safe use of a partially automated system. Hence why the longitudinal study design provides more robust results, as it addresses both of these aspects by providing an overall number of fixations and an understanding of how these changed during the trial week.

The combination of the study's three objectives allows for the classification of information usage to begin to understand how information usage changes over time in a partially automated vehicle and to inform the design of an adaptive interface. The next section will discuss the results of each objective in turn.

1) OVERALL PERCENTAGE OF TIME FIXATING ON INFORMATION DISPLAY

The results suggest that there was no statistically significant difference in the extent to which participants were using the information presented to them. Previous eye-tracking studies have reported a range of percentages of time spent looking at an in-vehicle display such as 4.3% [59] to 11.24% [60]. The figures reported in this study are lower than those reported in other studies but within a similar range. However, these previous studies used a manual driving task and not a steady-state partially automated system.

This study found that monitoring the roadway remains the most popular method of supervising the automated system. Given that there was no noticeable increase in the use of the information display over studies concerned with manual driving, it may suggest that the driver fixation patterns are analogous. This may be problematic as the information presented in partially automated vehicles is an important factor in how safely and appropriately a driver uses the system [10]; consequently, drivers may need to spend a higher percentage of time using the information display than is observed in this study.

However, to date, there are no agreed quantitative figures on how long a driver should fixate on the information display in a partially automated vehicle. If the driver's natural tendency is to monitor the roadway, then an interface must be able to take advantage of the limited fixations to it, to present the most appropriate information. With adaptive interfaces being touted as a solution to this challenge, the next section begins to classify the information that participants fixated on the most.

2) OVERALL FIXATIONS TO INFORMATION ICONS

It should be reiterated that these results are only applicable to steady-state driving, and it is likely that during more varied scenarios, certain information icons will become of increasing importance to the driver. For example, when the vehicle's battery is low, it is likely that the Battery icon will draw more fixations. However, as previously discussed, given that steady-state driving is likely to be the most frequent mode of operation in partially automated vehicles, this study sought to classify information usage for this particular context.

A key contribution of this study's fixation results is the finding that the most fixated single information icon was the Action Explanation. This may be because Action Explanation was textual, requiring more time to read. However, the non-significant differences in the average single fixation durations suggest that the textual form did not have a noticeable effect on salience when compared to the other information icons.

Furthermore, it has been previously found that participants require clear communication of a vehicle's capabilities [11]; specifically the communication of technical competence, by explaining what the vehicle is doing and why, has been found to be effective [61], [62]. The results from this study confirm that participants consistently fixated on information that provided an explanation as to what the vehicle was doing and why it was doing it. Importantly, at the time of writing, the authors are not aware of any partially automated vehicle, either on the market or in development, that provides action explanation on its information interface. This study shows that this specific information is of importance to users in order to help them understand the capabilities of their partially automated vehicle.

The second most popular information icon was the Hazard Scanner. This information was focussed on the future state of the vehicle and depicted the vehicle's perceived path and hazards in the near future. This indicates that participants were engaged in the monitoring task, using the most detailed information to confirm the vehicle's operation. Conversely, the Battery icon had the fewest fixations. Though this was to be expected as the battery level of the vehicle is not as imperative in a simulated environment as in the real world.

By the overall fixation results alone, this would suggest that the Battery is the least important information icon; however, that is contrary to evidence that found presenting an accurate measure of the range and capacity of an electric vehicle's battery was crucial for driver trust [63]. At this point, this study's unique longitudinal design must be considered. This gave the fixation data a greater depth and allows the results to be placed into the greater context of how fixations changed over time, indicating what information icons should remain of prominence on an adaptive display, and what should be reduced.

3) CHANGE IN INFORMATION FIXATIONS

The final set of results provide the context to understanding how information usage in a partially automated vehicle changes over time.

Firstly, the study highlighted the methodological benefits of the longitudinal study design, which better reflects the interaction with an HMI in real-world driving. Results from this study suggest that studies using a single exposure design are unlikely to be truly representative of a participant's interaction with an HMI over time.

Based on the previously discussed eye-mind assumption, information that exhibited a statistically significant increase or decrease should be adapted in prominence accordingly on a future adaptive HMI. Conversely, information which showed no statistically significant change in fixations should remain consistent in their relative prominence on the display. Three information icons exhibited significant changes in fixations across the trial week, suggesting information could be adapted on a future interface. The other remaining information showed no statistically significant change in fixations, indicating that these should remain the same in their relative prominence on an HMI.

The Automated Driving Indicator increased significantly in fixations, suggesting participants appeared to become accustomed to the partially automated system to the point that a simple confirmation of technical competence was adequate.

Conversely, the Hazard Scanner exhibited the largest significant reduction in fixations, but the overall fixation average remained high. The Hazard Scanner in this study presented the information as closely as possible to existing partially automated interfaces, and the results suggest that in its current design, the information will not be used by drivers after having used the vehicle for a period of time. Given the overall number of fixations were high, and the Hazard Scanner's importance to the safe use of a partially automated system, there would need to be consideration given to the design of this information, perhaps using other notification modalities. There was a similar trend with the Navigation information. Participants tended towards being less concerned about understanding the future state of the vehicle and would rather receive a confirmation of technical competence.

Overall, the results indicated that information related to system transparency either remained the same in usage or decreased significantly. On reflection, this behaviour is understandable. During steady-state driving, by definition, there are no events that require the participant to require future state information. On the contrary, the usage of technical competence information either remained the same or increased significantly. Initially, this is only applicable to steady-state driving, as this was the chosen scenario for this simulator study (as it is the most likely operational state for partially automated driving), and the vehicle was able to handle all the potential simulated conflict scenarios. The combination of steady-state driving within an automated vehicle may have resulted in reduced responsibility being placed on the user to act on future state information, i.e. users needing only confirm the system was working appropriately with technical competence information. This behaviour has been observed before and is the exact consequence of partially automated vehicles that this study aimed to address. Hence the contribution of this paper is extremely valuable in understanding how users change their information usage.

By using this understanding, it is possible to begin to inform the design of an adaptive HMI that can better support drivers in the use of partially automated systems. HMI designers should be wary that information considered highly important from a safety perspective (for example, the Hazard Scanner), tended towards lower usage during steady-state driving and there would need to be a method to account for this.

C. LIMITATIONS

A limitation is the sample size of 17. However, each participant provided five hours of eye tracking simulation data, which helped mitigate the impact of the sample size. Future studies should look to increase this sample size.

V. CONCLUSION

This study aimed to classify the information usage for drivers of partially automated vehicles and understand how these requirements changed over time with increased exposure to the system during steady-state driving; to inform the design of an adaptive interface. Information was selected using numerous models of human interaction to ensure a balanced presentation of information.

This paper is one of the first to explore the change in information usage in partially automated vehicles over multiple exposures. The temporal effects of familiarity with an automated system have previously been observed for factors such as trust and usability but had yet to be investigated for information usage. Furthermore, to date, this paper is the first to investigate information usage specifically for steady-state, monotonous driving.

Three key measures were taken- the overall percentage of time participants spent looking at the information display, the overall fixations to each information icon on the display and the change in fixations to each information icon over the course of the trial week. Using a combination of these three measures, preliminary guidelines as to how an adaptive HMI should adapt based on driver experience was proposed.

This current study shows that information categorised as system transparency, which informs the user on the future state of the vehicle, generally reduced in importance over time as the driver's familiarity with the automated system increased. Conversely, information on the technical competence of the vehicle (i.e. the confirmation of the current state) generally remained consistent in fixations. This is the first paper to characterise how a driver's information usage changes in partially automated vehicles and raises important questions about how interfaces should be designed in the future. Evidently, information like the Hazard Scanner provides detailed information intended to aid the driver's situational awareness but the results found participants tended towards using it less.

The key contributions of this work are twofold. First, the shortlist of information derived for partially automated vehicles is the first of its kind. These nine information icons were verified against three different models (SRK, PST and TM) to ensure the list could be considered representative of information needs in a partially automated vehicle. Secondly, by characterising how information usage changed, HMI designers can take these findings to develop future interfaces that can adapt information accordingly and better support the driver.

Future research will need to consider how this adaptive information transition should occur and the timescale over which the interface should adapt. From there, prototypes of an adaptive interface, based on the classifications defined in this study, should be produced and tested to assess the impact on driver performance and user experience.

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