Exploring the Behaviour of Distracted Drivers during Different Levels of Automation in Driving

David R Large [1*], Victoria A Banks [1], Gary Burnett [1], Sarah Baverstock [2], Lee Skrypchuk [2]

[1] Human Factors Research Group, Faculty of Engineering, University of Nottingham, UK
[2] Jaguar Land Rover Research, International Digital Laboratory, Coventry, UK
[*]david.r.large@nottingham.ac.uk

Abstract: Increased levels of automation in driving can reduce drivers' situation-awareness and cause erratic changes to workload and skills degradation following prolonged exposure. In addition, drivers (particularly those who are vulnerable to the onset of boredom/fatigue) may engage in non-driving related, and potentially distracting, secondary tasks. Understanding the behavioural cues associated with this change in driver state can assist in the design and development of future driver monitoring systems that intervene in instances where a driver exhibits 'high' levels of distraction. The aim of this study was to explore the behavioural cues associated with distraction caused by a non-driving related secondary task (pseudo-text reading) during manual, partially-automated and highly-automated driving in a medium-fidelity driving simulator. Results from thirty drivers show that highly-automated driving was characterised by reduced workload, increased secondary task times and longer in-vehicle glances, compared to manual and partially-automated driving. In contrast, partially-automated driving was characterised by high workload, poor secondary task performance and low levels of situation awareness. Furthermore, primary and secondary task performance immediately following take-over during partially-automated driving was significantly compromised. The results indicate that the same type of 'distraction' can elicit different behavioural cues depending upon the level of automation within driving. This information can be used to further the development of future driver monitoring systems.

1. Introduction

The prospect of autonomous vehicles that transport humans safely, reliably and economically has been applauded by automotive manufacturers and road safety campaigners as a potential solution to problems of driver distraction – if 'drivers' are no longer in control of vehicles, they cannot be distracted. However, this only holds true if the driver is completely removed from the driving task, as would be the case in a fully-autonomous system. While the driver remains embedded within the control-feedback loop to some extent (as is the case during 'partially-automated' and 'highly-automated' control), common risks associated with driver distraction (such as increased reaction times, decreased situation awareness in relation to a primary task, inappropriate driver responses etc.) may remain. While there have been considerable investigations regarding 'driver distraction' during manual driving – thereby enabling mediation strategies and/or interventions, including Driver State Monitoring Systems (DSMS) – the behaviour of 'distracted drivers' during periods of automation – and the potential ramifications if these drivers are required to resume manual control at some point – is less well understood.

Nevertheless, 'partially-automated' and 'highly-automated' solutions – including 'combined function' systems that automate both longitudinal and lateral control as well as some more strategic subtasks of driving (such as lane changes) – are necessary building blocks to further developments into both the technology and infrastructure required to realise fully autonomous vehicles. Therefore, until such time as fully autonomous vehicles have received widespread deployment and acceptance, understanding 'driver distraction' in the context of partially-automated and highly-automated control remains firmly rooted on the research agenda.

1.1. Levels of Automation

The driving task is made up of myriad individual subtasks [1, 2] that a human driver is traditionally required to undertake during manual driving. Automation of the driving task sees these roles and responsibilities increasingly undertaken by automated solutions. For example, vehicles are becoming progressively capable of sensing and interpreting input themselves, and in some instances, make decisions and suggest actions to the driver – if the driver fails to adequately respond to these suggestions, some vehicle features are further capable of performing actions autonomously without explicit consent from the driver (e.g. Autonomous Emergency Brake). The role of the driver within an automated driving system is therefore shifting from that of active operator to more of a passive monitor [3].

The allocation and demarcation of system functionality between the driver and automated subsystems has however been a contentious issue for some time. A number of automation taxonomies have been proposed to provide basic narrative descriptions of task allocation for different levels of autonomy. Whilst their definitions remain similar, they are often used interchangeably within the literature leading to confusion over what the driver and automated counterparts are ultimately responsible for. Even so, there is a consensual view that during the intermediate phases of automation, vehicle systems are not able to cope with all possible driving eventualities [4]. This means that the driver may be requested to regain control at any time (reflecting 'partial' automation) or within a predefined time-period (representing 'high' automation). In addition, human drivers retain ultimate responsibility for vehicle control, during 'partial automation', and must therefore permanently monitor the automated systems in order to be able to resume control. In contrast, during 'high automation', the need for permanent monitoring of automated systems is removed, but drivers must still be prepared to resume control with appropriate notice in situations not covered by the automated system [5].

Despite the intention of automated driving features to improve road safety, comfort and convenience [6], unintended consequences have been reported [7, 8, 9, 10]. There is already significant evidence to suggest that automation can lead to reduced situation awareness (SA) [11], erratic changes to mental workload [12, 13, 14], issues surrounding trust, complacency and overreliance (e.g. [15, 16, 14]), and skill fade (e.g. [17]). With both 'partially' and 'highly' automated driving requiring the driver to resume manual control in some situations, drivers must remain vigilant to changes in system behaviour and/or environmental conditions [5]. This places additional demands on the driver to maintain an appropriate level of SA so that they do not fall victim to out-of-the-loop performance decrements, particularly cognitive overload and underload [14, 18].

1.2. Driver Distraction and the Role of Driver Monitoring

The study of ‘driver distraction’ is confounded by the issue that there is no widely accepted definition of the terminology [19]. The International Standards Organisation (ISO) however provides a rudimentary definition of distraction as “attention given to a non-driving related activity, typically at the detriment of driving performance” [20]. During the driving task, drivers continually allocate their attention to both driving and non-driving tasks. Most of the time, drivers are successful in dividing their attentional resources between concurrent tasks without any serious consequences to their performance. They are also capable of adapting their driving to meet the demands of the environment as long as they maintain a good level of SA (e.g. compensatory behaviours such as reducing speed or avoiding risky manoeuvres) [21]. However, sometimes drivers can be distracted by activities or events that lead them to inadequately divide their attention and subsequently compromise their driving performance [22]. Distraction is therefore strongly associated with accident involvement and near-misses [23]. In-vehicle distractions specifically have been shown to reduce SA [11] but increase the subjective perception of workload [24]. Dingus et al. [25] and National Highway Traffic Safety Administration [26] estimate that anywhere between 16% and 80% of crashes are directly or indirectly linked to driver distraction. Being distracted from the primary task of driving can therefore be one of the most dangerous errors that a driver can make [27].

Whilst the sources of distraction may take many forms, researchers agree that there are four basic types of distraction; visual, auditory, biomechanical and cognitive distraction [28]. Regardless of the type of distraction, Lansdown et al. [29] argue that it will almost always prove to be detrimental to driving performance. However, the ‘type’ of distraction is an important factor into how far drivers become distracted from the primary task at hand and their subsequent performance. For example, tasks that rely upon the presentation of visual information can increase the amount of time drivers look away from the road (visual distraction) whereas other tasks may have no visual component (non-visual distraction) [23]. Increased eyes off road time has been shown to increase lateral deviation from the centre of the lane (e.g. [30]) and some studies have also shown changes to longitudinal control. For example, compensatory behaviours such as reduced travel speeds and increased time headways to lead vehicles have been reported (e.g. [31]). There have also been some conflicting results in terms of driver responses to discrete events when they are visually distracted. Some studies report increased reaction times to lead vehicle braking (e.g. [32]) whilst others show no differences (e.g. [33]). Regardless, it is well established that engagement in a secondary task whilst driving can distract drivers and compromise driving safety.

As increasing levels of automation are introduced into the driving task, the likelihood that drivers will engage in secondary tasks also increases [34, 35]. This is particularly problematic for 'partially-automated' systems as drivers may become vulnerable to the onset of 'out-of-the-loop' performance problems [7, 8, 9, 10]. For example, the Office of Defects Investigation [36] cite that an "extended period of distraction" was the probable cause of a fatal crash involving a Tesla Model S being driven in 'Autopilot' mode. Traditionally, designers have been able to use vehicle control inputs as an indicator of driver state (i.e. lane position and headway data automatically collected via the CANBUS). However, these data become irrelevant when automation is incorporated into the system, primarily because automation essentially stabilises vehicle control inputs leading to more uniform and consistent driving behaviour. The purpose of a DSMS in this context is therefore to identify the different behavioural cues of the driver to *infer* distraction or fatigue [37], so that steps can be taken to re-engage the driver with the driving task if required. However, questions remain over the validity of these systems and the measures in which they employ. Gonçalves & Bengler [37] outline a set of metrics that are associated with distraction detection. For visual distraction, these include glance patterns, mean glance duration and 'eyes-off-road' time. Mean glance duration can be used to infer the level of task engagement/distraction by means of gaze time allocation on different areas of interest (AOI) within the vehicle [37]. This means that higher mean glance duration values could be used to infer the state of the driver (i.e. higher values for visually-distracted drivers). In contrast, auditory distraction can be inferred using measures of pupil diameter [38] and blink frequency [39] whilst biomechanical distraction can be inferred using measures relating to posture (e.g. head direction, [40]).

Employing a DSMS within partially-automated or highly-automated vehicles requires that these systems understand the behaviour of 'distracted drivers' in the context of automated control. A further requirement is to understand how this behaviour differs dependent upon the level of automation employed.

1.3. Overview of Study

To explore driver distraction in the context of automated driving – and to identify whether the level of automation impacts upon the behavioural cues exhibited by distracted drivers – we conducted a simulator study in which drivers were invited to complete a secondary pseudo-text reading task – specifically chosen to induce visual distraction – during increasing levels of automation. Participants were instructed to undertake the secondary task only when they felt safe to do so.

The pseudo-text reading task (recognised in international standards [41] and previously employed by the authors in [42]) involves searching for a target character amongst random strings of characters, presented to appear as words. This mimics actual reading in the sense that the participant is instructed to scan from left to right and top to bottom, but it removes the requirement for higher level processes involved in comprehension. Therefore, one of the main advantages of using pseudo-text as opposed to normal text is that it completely removes any variation caused by introducing semantic information. Furthermore, eye-movements when reading pseudo-text have been shown to resemble eye-movements during normal reading [43].

In addition to measuring secondary task performance (task time, success rate), drivers' eye-movements, driving performance and physiological state were monitored, and subjective ratings of workload and situational awareness were invited following each drive.

2. Method

2.1. Participants

Thirty people took part in the study: 18 male, 12 female, with an average age of 35.9 years. All participants held a valid driving licence and were experienced and active drivers (mean time with licence, 16.5 years). Participants were self-selecting volunteers who responded to advertisements placed around the University of Nottingham campus and were reimbursed with shopping vouchers as compensation for their time. All participants provided written informed consent.

2.2. Apparatus, Design and Procedure

The study took place in a medium-fidelity, fixed-based driving simulator at the University of Nottingham (Figure 1). The simulator comprised the front half of a right-hand drive Honda Civic car positioned within a curved screen affording a 270° viewing angle. A bespoke driving scenario was created, using STISIM (v3) software, to resemble a standard three-lane UK motorway, and projected onto the screen using three high definition overhead projectors. Participants were instructed to follow a lead vehicle, and remain within lane one for the entirety of the experimental drive unless instructed otherwise by the Experimenter.

Figure 1 - Medium fidelity driving simulator showing motorway scenario used during study

Participants undertook six drives (counterbalanced), with each drive lasting between 6 and 12 minutes. These drives represented three different levels of automation:

1. Manual – participants were responsible for manually controlling all aspects of vehicle control at all times (as would be expected in the real world).
2. Partially-Automated – the system took over lateral and longitudinal control (i.e. steering and speed control/braking) at regular intervals throughout the journey, but participants remained responsible for permanently monitoring the system and were instructed that they may be required to resume complete control of the vehicle at any time.
3. Highly-Automated – the system took over lateral and longitudinal control (i.e. steering and speed control/braking) throughout the majority of the journey. The participant was told that they did not need to permanently monitor the system while it was active, but may be requested to take over control within a predefined time-frame.

Each condition was explained to participants exactly as described above, although they were unaware how frequently they would be required to resume/relinquish manual control during the drives that employed automated control – this actually occurred on five occasions during the partially-automated drive, whereas manual control was only required to start and end the highly-automated drive. Instructions to hand-over control (from manual to automated and vice versa) were provided using an audio voice prompt and three auditory tones. There were no physical cues presented within the environment to indicate the imminent hand-over or resumption of control. Participants were given the opportunity to experience a practice drive using partially-automated and fully-automated systems so that they could familiarise themselves with the simulator controls and hand-over/hand-back procedure prior to the commencement of testing.

Participants were exposed to each of these conditions twice – once with a nominally-assigned pseudo-text secondary task of varying task difficulty (‘easy’ with 2 lines of pseudo-text and ‘difficult’ with 5 lines) and once with no secondary task (providing baseline data); the drives were counterbalanced in order to avoid learning effects. For each task, the pseudo-text task was displayed as a complete passage (e.g. Figure 2) at approximately 5 minute intervals throughout each drive using a HP EliteBook screen located in the centre console of the car; for the partially-automated drive, an equal number of occurrences appeared during automated and manual episodes of driving. This task was self-paced and the pseudo-text therefore remained on screen until participants had completed each task. Participants were asked to scan the text, left to right, top to bottom (as if reading), and count aloud how many occurrences of the capital “E” existed on the screen. They were encouraged to complete the task as quickly and accurately as possible, but only to undertake the task when they felt it was safe to do so. Answers were recorded manually by an experimenter. Onset of the secondary task was signalled via an auditory tone.

2.3. Measures

Throughout the drive, behavioural indicators of visual distraction were captured. These included secondary task performance, glance behaviour and physiological measures (inter-beat interval, IBI, as an indicator of workload). Glance behaviour was captured using SMI Natural Gaze Eye-Tracking Glasses whilst physiological data was captured using the Empatica E4 wristband. Driving performance metrics were also captured for the manual episodes of driving (i.e. the manual drive and the manual driving episodes of the partially-automated drive).

At the end of each drive, participants were asked to complete subjective assessments of workload (NASA-TLX [44]) and situation awareness (SART [45]). For the partially and highly-automated driving conditions, these subjective assessments were completed twice (i.e. to relate to ‘easy’ and ‘difficult’ pseudo-text secondary tasks) to enable a direct comparison of workload and SA between different levels of secondary task difficulty.

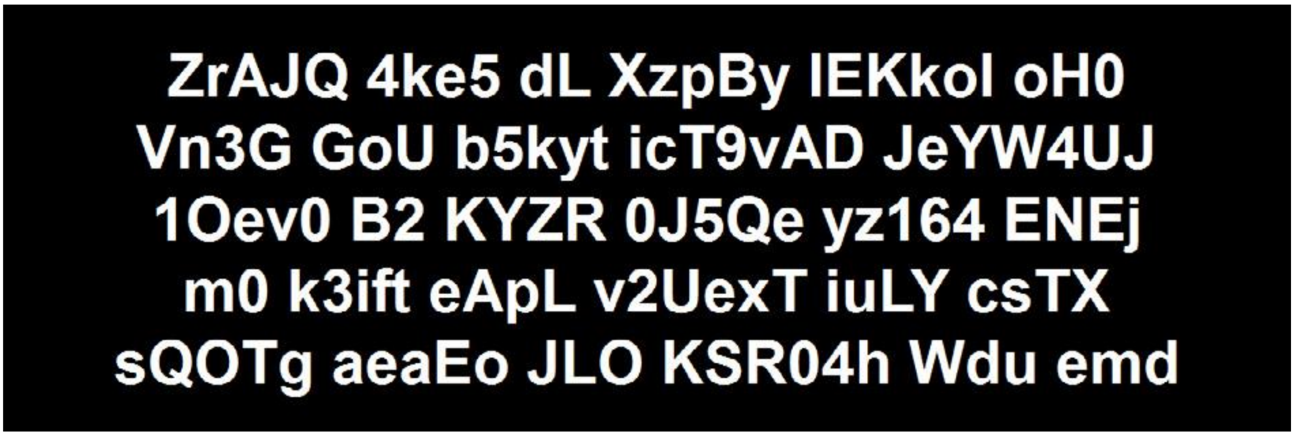

Figure 2 – Example of ‘difficult’ pseudo text employed during study

3. Results and Analysis

Results are presented and analysed below. Unless otherwise stated, repeated-measures ANOVAs were conducted for each measure, with Bonferroni-corrected pairwise comparisons, where appropriate. Graphs show standard error bars unless otherwise stated.

3.1. Driving Performance

There was a significant main effect of Drive (manual, partially-automated) for Standard Deviation of Lane Position (SDLP) ($F(1,90)=9.87$ p = .002) and Task Complexity (none, easy, difficult) ($F(2,90)=14.33$ p < .0005) and a significant interaction between Drive and Task Complexity ($F(2,90)=5.23$ p = .007). SDLP was higher for the manual episodes of control during the partially-automated drive, compared to the manual drive (p = .002) (Figure 3). SDLP was also significantly higher when participants were undertaking the pseudo-text secondary task (either easy or difficult) compared to no task (p_{max} < .0005) (Figure 3).

For Standard Deviation of Head Way (SDHW), there was a significant main effect of Drive ($F(1,90)=7.90$ p = .006) revealing that the variability in headway was significantly greater during manual driving compared to manual episodes of driving during partially-automated control (p = .006) (Figure 4). There was also a main effect of Task Complexity ($F(2,90)=7.87$ p = .001), with difficult tasks encouraging greater variability in headway than when no tasks were undertaken (p < .0005) (Figure 4).

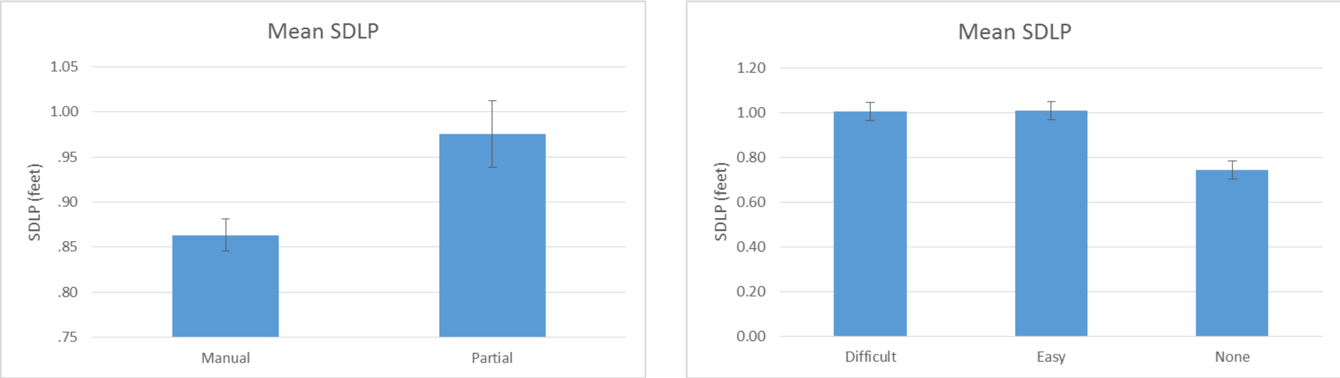

Figure 3 – Mean standard deviation of lane position (SDLP) shown by drive type (left) and secondary task complexity (right)

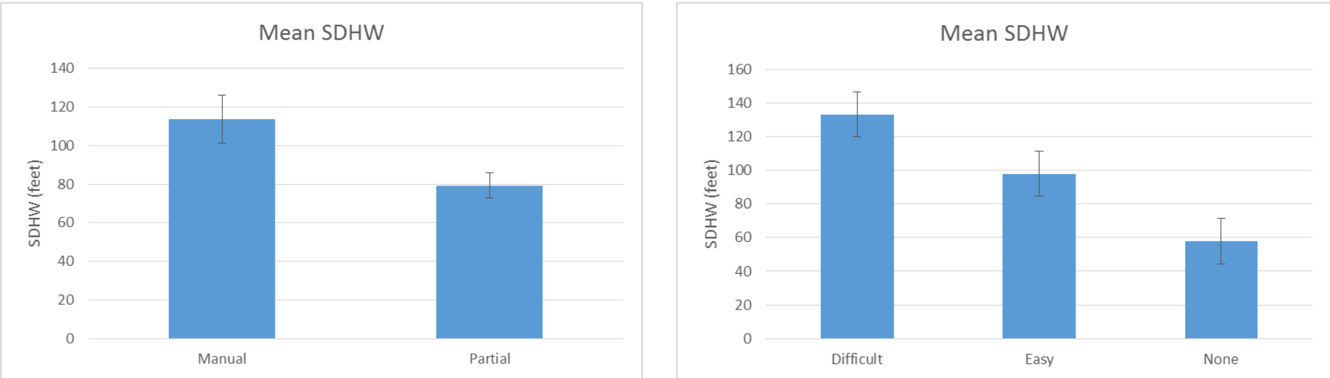

Figure 4 – Mean standard deviation of headway (SDHW) shown by drive type (left) and secondary task complexity (right)

It is perhaps unsurprising that conducting a secondary task while driving had an impact on vehicle control, with higher SDLP and SDHW evident during difficult tasks in particular. Perhaps less expected though is that there was generally greater variation in vehicle control measures (i.e. SDLP) during the manual episodes of the partially-automated drive. This may be due to behaviour associated with participants resuming control e.g. re-establishing what they believed was an appropriate headway/speed, but may also have been influenced by carry-over effects (e.g. poor speed calibration) from the periods of automated driving.

3.2. Secondary Task Performance

Secondary task performance (speed, accuracy) was compared across manual, partially-automated (manual), partially-automated (automated) and highly-automated drives, as well as between easy and difficult tasks. For task time, there was a significant main effect of Drive ($F(3,90)=33.49$ p < .0005), with pairwise comparisons revealing that secondary tasks were completed significantly quicker during the partially automated drive (both manual and automated episodes) compared to manual and highly-automated drives ($p_{max} < .0005$) (Figure 5). The potential for control transitions to take place at any time may go some way in accounting for these differences. Shorter secondary task times overall associated with partially-automated driving suggest that participants felt rushed to complete the task so that they were prepared to resume control if necessary. In addition, eye-tracking results for the partially-automated drive, though significantly different, were more closely aligned with manual driving than highly-automated driving, suggesting that drivers were confronted with similar 'divided-attention' task allocation and prioritisation conflicts during partial-automation.

It is also of interest that secondary task times during the highly-automated drive were significantly longer than the partially-automated drive (both manual and automated phases), suggesting that drivers took greater care when completing secondary tasks in situations of highly-automated control as they were not required to permanently monitor the driving task/automated system (Figure 5). Results confirm that there was a significant effect of Drive for success rate ($F(3,90)=5.16$ $p = .002$), with pairwise comparisons revealing that greater success was achieved during automated driving (both highly-automated and the automated periods of the partially-automated drive) compared to manual episodes of driving during the partially-automated drive ($p = .024$ and $.022$, respectively) (Figure 5). Higher success rates could signal that the driver was more heavily engaged in the secondary task and therefore distracted from the primary task. The highest secondary task success rates and longest in-vehicle glances observed during high-automated driving supports this strategy.

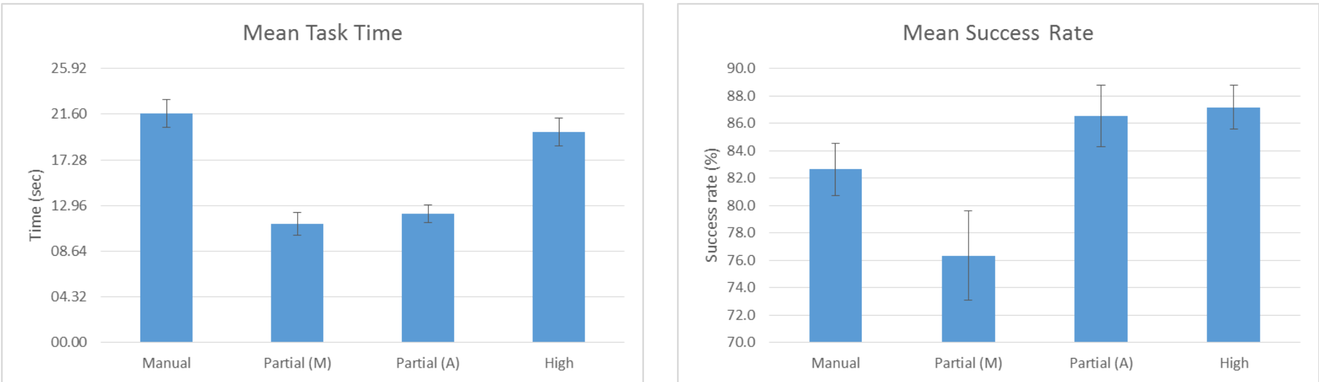

Figure 5 – Secondary task performance: mean task time (left) and mean success rate (right)

3.3. Glance Behaviour

For mean glance duration (MGD), there was a significant main effect of Drive ($F(2,50)=53.7$ $p < .0005$). There were no significant differences based on Task Complexity ($p = .32$). MGD associated with the manual drive was significantly shorter than that observed during the partially-automated and highly-automated drives (Figure 6). In contrast, the largest MGD was associated with fully-autonomous control. This suggests that the automation of longitudinal and lateral control provides drivers with increased attentional resources that enable them to take longer glances at specific areas of interest (AOIs) (in this case the screen used to display the secondary task).

There was also a significant main effect of Drive ($F(2,50)=86.1$ $p < .0005$) for number of glances (NG), but no significant differences based on Task Complexity ($p = .31$). Significantly more glances made during the manual drive than during the partially-automated drive, and more during the partially-automated drive compared to the highly-automated drive (all $p < .0005$) (Figure 6).

For total glance time (TGT), there was also a significant main effect of Drive ($F(2,50)=26.9$ $p < .0005$), but no significant differences based on Task Complexity ($p = .15$). There was also a significant interaction between Drive and Task Complexity ($F(2,50)=3.53$ $p = .037$), revealing that TGT was significantly shorter during the manual drive than during the partially-automated drive, which in turn was significantly shorter than the highly-automated drive (all $p < .0005$) (Figure 6).

Based upon these results, we can conclude that the symptoms of a distracted driver include increased MGD, increased TGT and reduced NG. All such behaviours become more pronounced as the level of automation increases.

3.4. Physiological Behaviour

There were no significant differences associated with Task Complexity ($p = .23$), nor Drive ($p = .77$) for mean and standard deviation of inter-beat interval (IBI), (Figure 7), suggesting that in this study at least, IBI was not deemed a useful indicator to use in the measurement of workload/driver distraction.

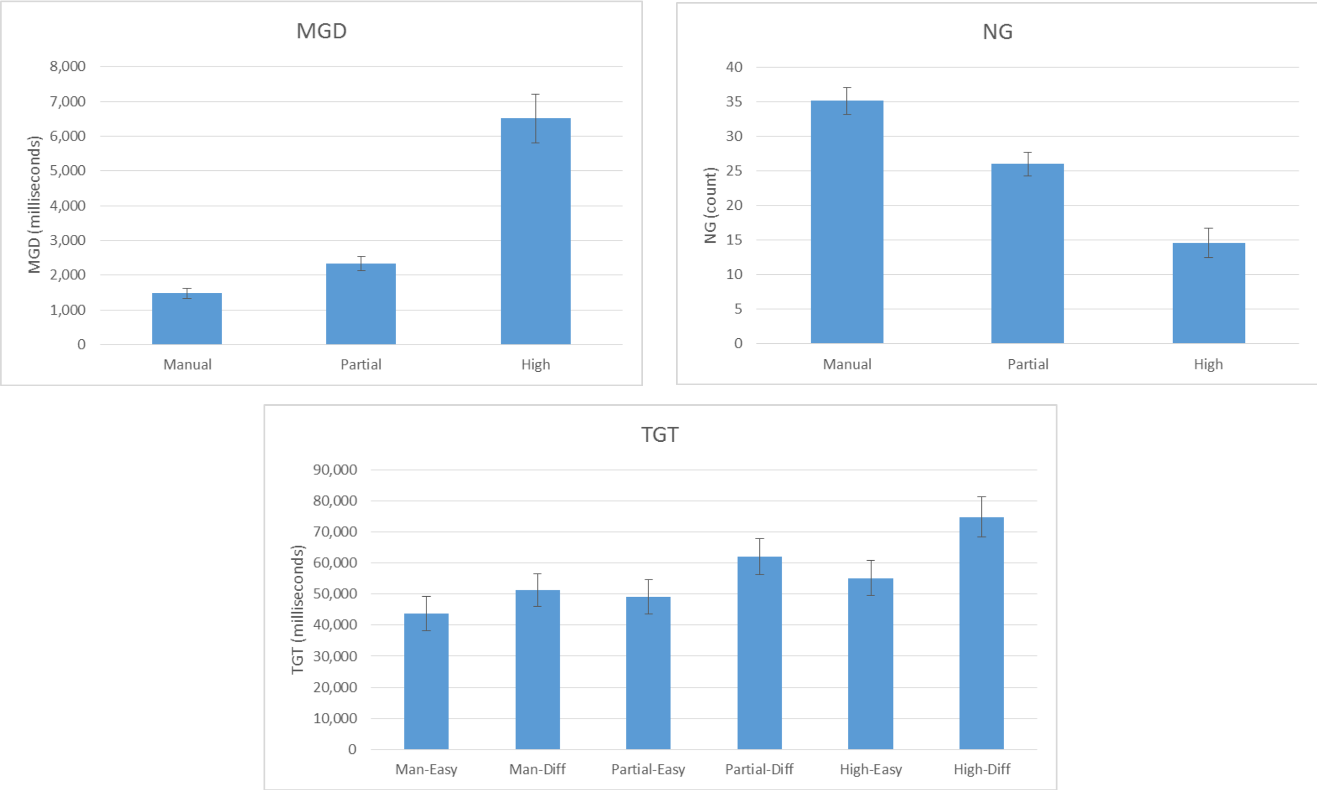

Figure 6 - Glance behaviour, showing MGD (top left), NG (top right) and TGT (bottom)

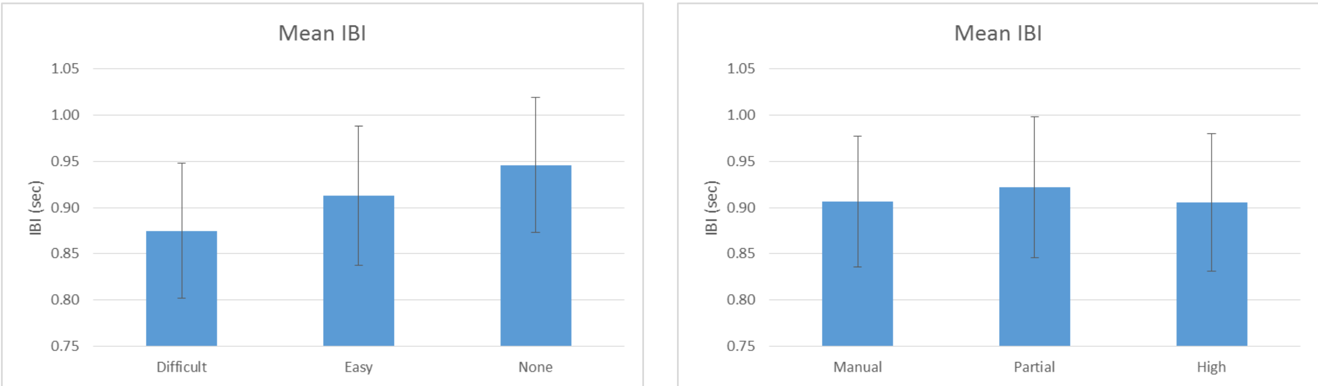

Figure 7 – Mean inter-beat interval (IBI), showing standard deviation bars, segregated by drive (left) and task complexity (right)

3.5. Subjective Workload

Subjectively, there were significant main effects of Drive ($F(2,180)=97.4$ p < .0005) and Task Complexity ($F(2,90)=29.9$ p < .0005) and a significant interaction between Drive and Task Complexity ($F(4,180)=8.0$ p < .0005) for NASA-TLX overall workload. Workload ratings following the manual drive were significantly higher than those for the partially-automated drive, which in turn were higher than ratings following the fully-automated drive (p_{max} = .005). Higher workload in the partially-automated drive could, in part, be attributed to the additional demand placed upon drivers to maintain an awareness of the current, active driving mode. It seems likely that overall workload would have fluctuated greatly within the partially-automated drive – with lower workload associated with the automated phases of the drive and higher workload associated with the manual phases of the drive. However, the sensitivity of the measure employed is unable to confirm this. As to be expected, ratings for difficult tasks were significantly higher than easy tasks, which in turn were higher than situations when no secondary tasks were undertaken (p_{max} = .015).

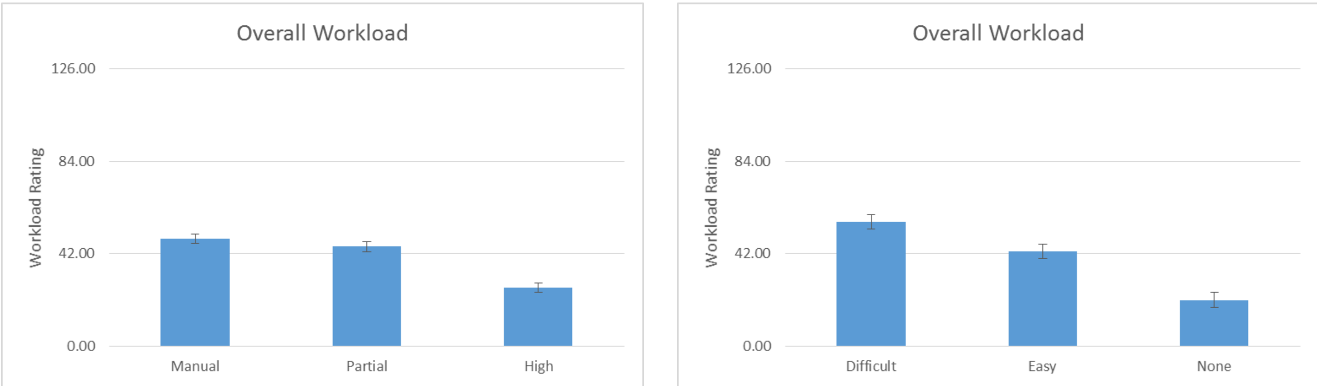

Figure 8 - Mean overall workload ratings segregated by drive (left) and task complexity (right)

3.6. Situation Awareness

Results of the SART questionnaire revealed that there were significant main effects of Drive (F(2,180)=5.31 p = .006) and Task Complexity (F(2,90)=16.6 p < .0005), indicating that SA was lower when secondary tasks were undertaken, with ratings associated with both easy and difficult tasks significantly lower than situations in which no secondary task was undertaken (p = .002 and p < .0005, respectively) (Figure 9). Additionally, participants rated SA highest during the highly-automated drive, with ratings during the partially-automated drive significantly lower (p = .005) (Figure 9).

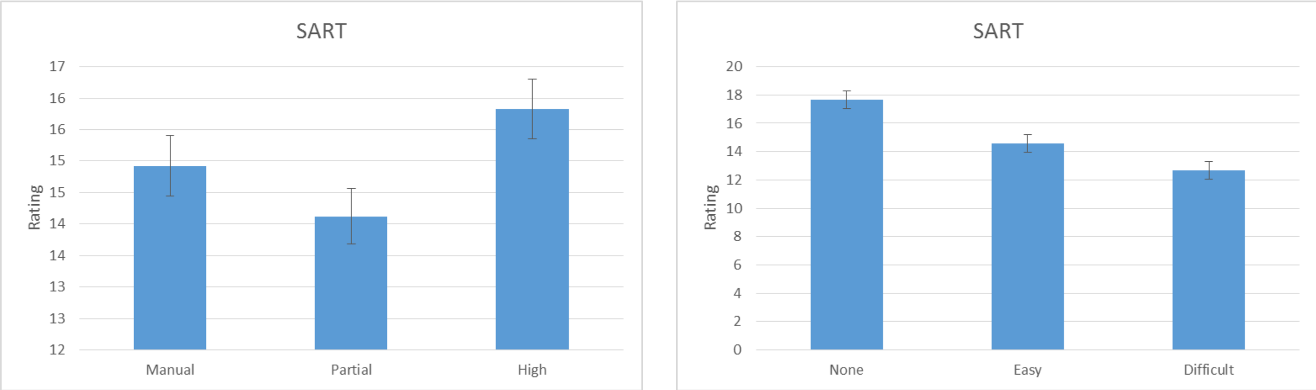

Figure 9 - Mean situation awareness (SART) ratings segregated by drive (left) and task complexity (right)

The elevated levels of SA associated with the highly-automated driving condition are unexpected, given the current literature that suggests increased levels of automation actually decrease driver SA. However, it is suggested that participants interpreted the SART questions based upon their perception of the secondary task, rather than the primary task of driving. Thus, elevated results indicate that drivers were far more 'aware' of secondary task performance. Of some concern were the results obtained for partially-automated driving, where we would expect drivers' SA to be similar to SA during manual driving. This is likely to be because drivers were required to permanently monitor the driving environment and be prepared to resume control of the vehicle at any point. The results from this study however suggest that drivers are vulnerable to reduced SA in such conditions. Reduced SA is problematic because it can lead to mode confusion and startle effects if control is handed back to the driver when they least expect it.

4. Discussion

The purpose of this study was to explore whether drivers who were visually distracted by the same task would elicit different behavioural cues depending upon the level of automation within the driving task. The study revealed that distracted drivers within highly-automated driving systems exhibited greatest MGD and TGT, fewer NG, as well as improved secondary task performance. Glance behaviours during manual and partial-automation were more erratic, characterised by decreased MGD and TGT but with much larger NG. This knowledge could be used to help inform the development of future DSMS. Of course, secondary task type will play a role in the type of behaviour elicited by the driver but the purpose of this study was not to investigate 'how' people get distracted. It is highly probable that patterns of behaviour relating to visual distraction, such as those discussed above, are generalizable to different secondary task types, but this requires validation.

The authors caution that a truly effective DSMS system should utilise numerous measures that can account for different distraction types as well as state types (distraction and fatigue). Visual distraction is after all measured differently to auditory distraction, and fatigue assessment utilises different measurements entirely to distraction. DSMS currently rely upon eye-based metrics in conjunction with driving performance to infer driver state [37]. However, the sophistication of eye tracking technology means that we should not rely upon glance behaviour alone to infer driver state. This is because it is not always possible to reliably track an individual's eye movements. For example, Kok and Jarodzka [46] cite that individuals who wear contact lenses or glasses cannot always be reliably tracked. There could therefore be issues associated with the quality of data that is collected.

Similarly, the quality of data generated from physiological measures within driving could also be an issue. Whilst there appeared to be a lack of differentiation in the physiological data collected in this study, effects may have been masked. For example, the secondary tasks were generally short in duration (between 10 and 20-seconds), so differences may have been diluted by considering mean values. Regardless, it would be difficult to say with certainty that any difference in physiological data would have been a result of 'distraction' rather than some other variable. It is possible that physiological data could have varied between all driving conditions for different reasons. For example, during the partially-automated drive, participants were regularly required to hand-over and take-back manual control, and were thus instructed to remain vigilant. This may have created some anxiety about understanding which driving state was currently active and maintaining awareness, which could have elevated physiological indicators. In addition, in a real-world DSMS, wearable technology could be considered to be invasive by drivers and therefore not accepted. More research is needed therefore to explore novel approaches to the collection of driver physiology in this application.

As a final note, it is worth highlighting that participants were largely unfamiliar with the automation as presented in the driving simulator. In addition, results were obtained from relatively short-term exposure. Although the behaviour of novice drivers remains a perfectly valid research strategy (in so far all drivers will be unfamiliar with automation when they first encounter it), further longer-term studies that expose participants to partially-automated and highly-automated systems over extended periods (potentially with secondary activities more closely related to their own personal lifestyles/choices) are recommended.

5. Conclusions

The results of this study show that the symptoms of visual distraction in an automated vehicle, particularly during partial-automation, differ to that of manual driving. The presence of different behavioural cues depending upon the level of automation is an interesting finding. For example, if drivers display behaviour more akin to that associated with highly-automated driving situations, when they are in fact operating at a lower level of autonomy, re-engagement strategies could be implemented, although further work is required to fully classify behavioural cues in each situation.

6. Acknowledgements

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