7th International Conference on

Driver Distraction and Inattention

Disconnected drivers during manual, assisted, and automated driving

Online

18-20 October 2021

BOOK OF ABSTRACTS

The DDI2021 conference will take place online on 18-20 October 2021

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About DDI2021

Welcome to the 7thInternational Conference on Driver Distraction and Inattention (DDI2021). DDI2021 will be held in Lyon, France, on October 18-20, 2021, and follows the six highly successful DDI Conferences held previously in Gothenburg, Sweden (2009, 2011, 2013, 2018), Sydney, Australia (2015) and Paris, France (2017).

The International Conference on Driver Distraction and Inattention (DDI2020) is the premiere international event on this topic, attracting delegates from more than 20 countries. It is designed to bring participants – from academia, industry and government – up-to-date on current and recent developments and trends in the field of inattention and distraction in driving.

The conference topics include theory, measurement, effects, crash risks, and prevention/mitigation related to driver distraction and inattention. Moreover, DDI2020 will focus on the driver/occupant status. Participants are invited to present and discuss work covering disconnected drivers in assisted (drowsiness, out-of-the-loop, overreliance), and in autonomous vehicles (sleeping, take overs, etc). The new distraction legislation related to autonomous driving will also be given pride of place this year.

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What Just Happened? Exploring Drivers' Acceptability of Minimal Risk Condition – A Qualitative Driving Simulator Study

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Keywords: Automated Driving, Driving Simulator, Minimal Risk Condition

ABSTRACT

Automated vehicles (AVs) are expected to improve road safety by reducing the number of collisions and safety critical events [1,2]. In the event of a failure of the automated driving system (ADS), or if it reaches the limit of its capability, action is required to preserve the safety of the vehicle occupants and other road users. The Society of Automotive Engineers (SAE) [3] highlights the need for the user to assume control in these situations by performing the driving task or placing the vehicle in a safe state, i.e. one in which the risk of a collision is reduced ('minimal risk condition' (MRC)). Should the driver not be available or deemed unable to achieve this (for example, if they are inattentive or distracted by a non driving-related task (NDRT)), the ADS (operating at level 4 or above) must achieve the MRC. MRC is therefore the subject of intense scrutiny, with many automotive manufacturing companies (OEMs) already proposing solutions, for example, by performing a controlled stop of the car at the side of the road (a 'minimal risk manoeuvre' (MRM)). This is arguably an extension of existing advanced emergency braking systems (AEBS) that sense driver inactivity or their lack of an adequate braking response and intervene. However, one of the key differences in a L4-AV is that drivers are "out of the loop" by design (i.e. not driving and engaged in a NDRT), and the MRM may therefore be entirely unexpected. As such, drivers' responses and behaviour are unpredictable. For example, the ADS will likely prohibit driver intervention during the MRM [3], but it is unclear whether the driver would expect or attempt to intervene and what the consequences might be. These factors are likely to influence the acceptability of proposed solutions.

In a medium-fidelity driving simulator, sixteen experienced drivers (10 female, 6 male, 21-65 years old, mean age 31.8, mean driving experience: 12.0yrs with licence, 4.0 hrs/wk driving) undertook three 8-minute drives, each within the same simulated environment created using STISIM Drive software (v3). The driving simulator mimicked an SAE level 4 AV in that it was capable of monitoring the environment and executing both lateral and longitudinal control, thus relieving the driver from primary driving tasks. The MRM was achieved by changing lanes and bringing the vehicle to a stop outside the active traffic lanes (on the "hard shoulder") – a commonly proposed

MRC strategy [4]. Lane change trajectories and brake intensity were based on relevant literature [5,6,7], and vehicle controls were functionally disabled during the MRM. Automation was available only on lane two of a two-lane dual carriageway – representing the operational design domain. The first two drives included routine take-overs. During the third drive, participants were actively engaged in a secondary task – an immersive game on an iPad. This ensured they were "distracted" and subsequently failed the attentiveness assessment made by the 'driver monitoring system' (i.e. the experimenter) immediately prior to the takeover request, thereby initiating the MRM. This was communicated via an HMI located in the centre console and an accompanying spoken warning: "*You are inattentive, a safe stop will begin in 5 seconds*". Participants were made aware of the level 4 capabilities of the vehicle, with regard to routine operation, but were not informed of the MRM or MRC to avoid influencing their instinctive behaviour and responses. The study was video recorded for subsequent analysis. In a post-study interview, participants were asked to elucidate on factors such as: their initial response to the MRM, their understanding of the situation (what just happened?), the role they assumed, and the level of control they had or felt they should have (i.e. should they be able to intervene during the MRM). This paper briefly introduces six themes which emerged through inductive thematic analysis [8] of the transcribed responses to all questions.

1. Reluctance to Relinquish Control. Several participants felt that the intervention was abrupt and 'over the top' (p2,5,12), evoking negative emotions of "anger" and "frustration" (p2,3,14,15) or "panic" and "surprise" (p5,10,13); others referred to the process of the vehicle taking over control as "weird" (p6,12). Some stated that they subsequently felt the need to define and adopt a specific role during the manoeuvre, thus enabling a semblance of 'being in control' (e.g. monitoring the system performance), while others admitted that they waited for the system to instruct them.

2. Loss of Authority and Control. Participants expressed concerns regarding the removal of active control and decision-making authority. Some were frustrated by their inability to 'correct' the inattentiveness assessment ("*I am here and ready to drive*" (p3)), while others (p7) specifically identified that control had been removed without their consent, and therefore expected that it would be reinstated if they actively engaged with the driving task (e.g. pressed a pedal), as might be expected with existing driver assistance systems, such as cruise control. Others expressed the desire to be given a choice in the course of action.

3. Sensemaking. Although participants were initially unsure of what was happening, they were generally forgiving of the experience once they understood that it had been triggered by their lack of attention, and ultimately accepted that it probably represented the best (safest) course of action (p5,9,14). Nevertheless, concerns were expressed regarding the potential disruption it could cause (e.g. delaying their journey) – although this was regarded as an acceptable consequence by some (p4). It was also recognised that manually intervening during the manoeuvre could have a disruptive or deleterious outcome, and this stopped some participants from attempting to do so (p8).

4. Mental Models of System Capability. Drivers' mental models affected the level of trust they placed in the system. Scepticism about AVs generally, translated to distrust in the MRM (p8), although the experience already provided during the routine drives/handovers also shaped opinion ("*this is the first time it was changing lanes, so I didn't trust the car*" (p9)). For others, the ability of the car to take over control when their own attention lapsed *increased* their trust in the system (p4). The means by which driver attention was assessed was also questioned: "*I just glanced away and it suddenly said oh you're not attentive*" – assumes glance behaviour (p2). Another thought that their attention was determined by hands-on-wheel (p7), resulting in this driver fervently grasping the steering wheel. Others expected that the check involved a more thorough assessment, acknowledging the limitations of human performance ("*maybe ... you think you are alert enough to drive but you are not actually*" (p9)).

5. Perception of Drivers' Capability. Participants were generally in favour of their own abilities to take control, over and above those of the automated system and indeed, other drivers. This was consistently used as justification for their desire (and expectation) to intervene *during* the MRM (p4,6,8,15). Amongst those drivers who perceived the automated system as more capable than a human driver (p3,10,16), participant 3 even so highlighted that the system telling them they were not ready was annoying. Interestingly, several participants were supportive of the system controlling *other* drivers' unsafe behaviour (not necessarily their own!).

6. Situation Assessment. Participants regularly refereed to their own assessment of the driving situation, including factors such as 'complexity'. As such, many recognised that the MRC did not represent *complete safety*, but rather the best ("safest") course of action, under the circumstances. This also influenced their decision to intervene, with participants suggesting that they would more likely intervene if there was "*not much traffic*" (p5), for example. Conversely, others questioned how well the system would have performed had the road situation been more complex (higher density of traffic, different road infrastructure etc.), suggesting that this would ultimately determine their confidence, trust and the acceptability of the system (p11).

The study explored drivers' responses to a level 4 ADS-initiated MRC scenario using a simulated driving experience and follow-up interview, and presents themes that were identified from the interview data. Whilst most drivers ultimately understood the purpose of the MRM and appeared willing to accept it as the safest course of action under the circumstances, there was some initial confusion, resulting in strong emotional reactions, such as surprise and even anger. An interesting irony is that several drivers felt that they should have been consulted regarding the vehicle's intentions and actions – despite them being actively taken out of the control loop immediately prior to the take-over request. This suggests that drivers need to be made aware of the actions and intentions of their vehicle and indeed, *their own limitations* – at all times. In addition, the lack of control – or more precisely the removal of control without drivers' consent, and their inability to resume control partway through the manoeuvre (when some felt they were able to do so), appears to have frustrated drivers and presents a challenge to OEMs. Many of the concerns centred around drivers' preconceived ideas about AVs (i.e. their mental models), which, combined with elevated opinions of their own ability to resume control, suggest the additional need for improved driver training and awareness. Overall, the study highlights several key challenges to overcome before an enforced MRC may be seen as acceptable solution. Future work will aim to validate findings by analysing drivers' behaviour during the study.

References:

[1] Cunningham, M. L., & Regan, M. A. (2017). Driver distraction and inattention in the realm of automated driving. IET Intelligent Transport Systems, 12(6), 407–413. https://doi.org/10.1049/iet-its.2017.0232

[2] Serban, A. C., Poll, E., & Visser, J. (2018). Tactical safety reasoning. A case for autonomous vehicles. IEEE Vehicular Technology Conference, 2018-June, 1–5.

[3] SAE International. (2018). Taxonomy and Definitions for Terms Related to Driving Automation Systems for On-Road Motor Vehicles J3016_201806. https://doi.org/https://doi.org/10.4271/J3016_201806

[4]Dennis, E. P., Schultz, M., & Wallace, R. (2018). Opportunities to Encourage On-road Connected and Automated Vehicle Testing Recommendations for the Saginaw Region, (May).

[5] Yang, D., Zheng, S., Wen, C., Jin, P. J., & Ran, B. (2018). A dynamic lane-changing trajectory planning model for automated vehicles. Transportation Research Part C: Emerging Technologies, 95(June 2017), 228–247. https://doi.org/10.1016/j.trc.2018.06.007

[6] Large, D. R., Pampel, S., & Burnett, G. (2018). Exploring Drivers ' Visual Behaviour During Take-Over Requests Exploring Drivers ' Visual Behaviour During Take-Over Requests. In International Conference on Driver Distraction and Inattention (DDI2018). Gothenburg, Sweden.

[7] Pampel, S. M., Large, D. R., Burnett, G., Matthias, R., Thompson, S., & Skrypchuk, L. (2018). Getting the driver back into the loop: the quality of manual vehicle control following long and short non-critical transfer-of-control requests: TI:NS. Theoretical Issues in Ergonomics Science, 20(3), 265–283. https://doi.org/10.1080/1463922X.2018.1463412

[8] Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. Qualitative Research in Psychology, 3(2), 77–101. https://doi.org/10.1191/1478088706qp063oa

Effects of secondary tasks on drivers' glance and driving behavior while driving a partially automated vehicle on a closed circuit

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Keywords: Closed circuit, failure in longitudinal / lateral control, partially automated driving, secondary tasks, take-over maneuver.

AIM & SCOPE

In recent years, the automotive industry focused on increasingly automating the driving task to enhance driver safety by reducing human error [1], resulting in different levels of vehicle automation [2]. However, at this moment only intermediate levels of automation with limited capabilities and the requirement of constant supervision by the driver are available [3]. During partial automation (SAE level 2), the system is responsible for the longitudinal and lateral control of the vehicle, while the driver has to monitor the system, the environment and needs to take over the driving task completely without any take-over request, if the necessity occurs [2].

Even though vehicle automation might relieve some of the momentary driving demands, it does not inevitably lead to safer driving [4]. New issues arise due to the changing role from active driver to passive supervisor [5]. This change and the monotony of the monitoring tasks can result in reduced task engagement possibly leading to inattention, fatigue and cognitive underload, which in turn can trigger problems such as slower reactions or failure to intervene [6]. In addition, research showed that boredom and cognitive underload can result in increased secondary task engagement during automated driving [7, 8, 9], which is likely to cause other problems (e.g. reduced situation awareness, distraction), hence impairing potential safety benefits of different automation levels [9].

Studies evaluating the effects of secondary task engagement during automated driving often focused on higher automation levels [e.g. 3, 7] or are mostly executed in driving simulators [e.g. 1, 4, 6, 8]. The current study's goal was to evaluate the effects of different secondary tasks on the drivers' glance behavior and take-over performance while driving in a partially automated vehicle in a closed circuit environment.

METHOD

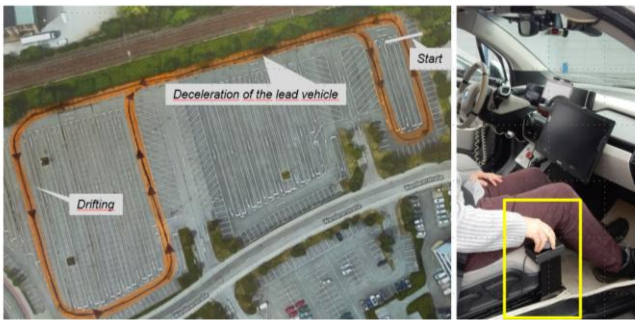
To safely investigate the effects of secondary task engagement on the participants while driving in a *real*, partially automated vehicle, the current study took place on a closed circuit that was situated on a parking lot in Chemnitz, Saxony (Figure 1).

Participants. *N* = 39 participants (18 female, 21 male), who were *M* = 40.38 years old (*SD* = 17.16, range 18-70 years) took part in the study. They all held a valid driver's license and drove *M* = 15,000 km (*SD* = 9,000 km) in the last year. Three participants were excluded from analysis due to technical problems.

Partial automation. Two vehicles were present on the circuit: the partially automated ego vehicle (maximum speed 27km/h) and a manually driven lead vehicle. The partial automation of the ego vehicle combined Wizard-of-Oz techniques with genuine automation: longitudinal control (acceleration and deceleration) was actually automated (i.e., maintained speed and distance automatically), whereas the experimenter on the passenger seat executed lateral control (steering) using a small steering wheel out of sight of the participants (Figure 1, right).

Take-over situations. Two different take-over situations, corresponding to possible errors in the longitudinal and lateral control, were examined. The situation *drifting* corresponding to the lateral control entailed the ego car drifting to the left. The situation *deceleration of the lead vehicle* corresponded to the longitudinal control and entailed the lead vehicle to decelerate without brake lights. Consistent with SAE level 2 automation [2], no take-over requests were issued, which required monitoring the system and environment to notice the take-over necessity. The experiment consisted of four trials (à 12 minutes), each consisting of five rounds on the circuit. In each trial, the participants experienced four take-over situations randomly assigned to the five rounds. Further, it was randomized which one of the two take-over situation occured. Due to limited space, involvement of two vehicles, and to enhance reproducibility, the take-over situations always took place on the same tract of the circuit (Figure 1, left).

Figure 1. Closed circuit with the locations of the take-over situations (left), Wizard-of-Oz steering execution out of sight of the participants (right).



Secondary Tasks. Of the four trials, three took place with and one without (baseline) a visual-manual secondary task. The three tasks were 1) the manual radio tuning task [10], which is used as reference task for manual driving, where the

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participants had to tune the radio to a predefined station; 2) watching news videos (length: 20s) followed by answering a question about the visual content; 3) text reading that requires scrolling followed by answering a questions about the content. The participants continuously engaged in one of the three tasks per trial. The order of the secondary tasks as well as the baseline trial was randomized.

Procedure. After reading written instructions about the study, the tasks and the take-over situations, the participants completed a manual and a partially automated familiarization drive. During the trials, the participants were filmed by cameras to collect glance behavior data. The driving performance was recorded though measuring technologies implemented in the vehicle. Participants filled out questionnaires after each trial to assess subjective experience.

Results. Regarding the glance behavior, the 10 seconds prior to a take-over situation were analyzed. Significant differences were found between the three secondary tasks regarding the mean glance duration (MGD), procentual gaze duration (PGD) and the number of glances (NG) to the task. Significantly fewer, yet longer glances were executed to the text reading task (NG: $M = 3.26$, $SD = 1.08$; MGD: M = 2.85s, SD = 1.49s; PGD: M = 74.71%, SD = 13.95%), compared to the video watching (NG: M = 4.11, SD = 1.04; MGD: M = 1.46s, SD = .55s; PGD: M = 56.29%, SD = 15.57%) and radio tuning task (NG: M = 3.76, SD = 1.05; MGD: M = 1.92s, SD = 1.15s; PGD: M = 61.24%, SD = 13.58%) that did not differ significantly. In addition, even though the participants did not allocate significantly fewer glances to the road during the task execution trials than the baseline trial, the on-road glances during task execution were significantly shorter (e.g. PGD: Baseline: M = 94.65%, SD = 6.34%; text reading: M = 24.69%, SD = 13.37%; radio tuning: M = 38.09%, SD = 12.64%; video watching: M = 42.98%, SD = 15.34%).

Regarding the take-over performance measures (e.g. reaction time or distance to lead vehicle), the results did not show significant differences between the three tasks and/or the baseline trial. There was, however, a significant difference between the two take-over situations regarding the reaction time: as expected, the participants reacted significantly faster to the *drifting* (M = 2.33s, SD = .89s), than to the *deceleration of the lead vehicle* (M = 9.45s, SD = 1.61s).

CONCLUSIONS

The study showed that different secondary tasks had distinctly strong effects on the drivers during partially automated driving. Compared to the baseline trial, the drivers allocated considerably less visual attention to the driving scene during secondary task execution. Especially text reading redirected considerably more visual attention to the secondary task. Video watching did not require as much attention and even less than the radio tuning task. A possible explanation for this observation might be that drivers simply listened to the video instead of looking at it. The take-over performance measures did not differ depending on the secondary task or the baseline trial. However, in a real driving situation the effects of the secondary tasks on the driver's attention might be much more detrimental than in this study. Especially, when more enticing contents such as YouTube videos or personal messages are involved.

Nonetheless, a promising methodological step was taken towards evaluating secondary task execution during partially automated driving.

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References:

[1] de Winter, J.C.F., Stanton, N.A., Price, J.S., et al.: ‘The Effects of Driving with Different Levels of Unreliable Automation on Self-reported Workload and Secondary Task Performance’ Int. J. Vehicle Design, 2016, 70, (4), pp. 297–324
[2] Society of Automotive Engineers International: ‘Taxonomy and definitions for terms related to driving automation systems for on-road motor vehicles’, SAE international, 2016
[3] Eriksson, A., Stanton, N.A.: ‘Takeover time in highly automated vehicles: noncritical transitions to and from manual control’, Hum. Fact., 2017, 59, pp. 689–705
[4] Stanton, N.A., Young, M.S.: ‘Vehicle automation and driving performance’, Ergonomics, 1998, 41, pp. 1014–1028
[5] Van den Beukel, A.P., van der Voort, M.C.: ‘Design considerations on user-interaction for semi-automated driving’, Proceedings of the FISITA 2014 World Automotive Congress, 2015, pp. 1–8
[6] Saxby, D., Matthews, G., Warm, J., et al.: ‘Active and passive fatigue in simulated driving: discriminating styles of workload regulation and their safety impacts’, J. Exper. Psychol.: Appl., 2013, 19, pp. 287–300
[7] Jamson, A.H., Merat, N., Carsten, O.M., et al.: ‘Behavioural changes in drivers experiencing highly-automated vehicle control in varying traffic conditions’, Transp. Res. C, Emerg. Technol., 2013, 30, pp. 116–125
[8] Carsten, O., Lai, F.C. H., Barnard, Y., et al.; ‘Control Task Substitution in Semiautomated Driving: Does It Matter What Aspects Are Automated?’, Human Factors, 2012, 54, (5), pp. 747–761
[9] Cunningham, M.L., Regan, M.A. ‘Driver distraction and inattention in the realm of automated driving’, IET Intell. Transp. Syst., 2017, pp. 1–7
[10] Krause, M., Angerer, C., Bengler, K.: ‘Evaluation of a Radio Tuning Task on Android while Driving’, Procedia Manufacturing 3, 2015, pp. 2642 – 2649. DOI: http://dx.doi.org/10.1016/j.promfg.2015.07.334

Assessing Neural Indices of Workload and Visual Engagement During Partial Automation

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Keywords: Attention; Automation; Electroencephalography; Theta; Workload; Alpha; Visual Engagement

ABSTRACT

One objective of vehicle automation is to mitigate distraction and inattention while driving. The Society of Automotive Engineers defines six levels of vehicle automation, ranging from Level-0, no automation, to Level-5, full automation [14]. Currently, vehicles with partial vehicle automation (i.e., Level-2) are publicly available and equipped with systems that maintain lateral and longitudinal control simultaneously. During Level-2 automation, drivers are required to remain engaged with the driving task, monitor the environment, and be able to safely regain control of the vehicle at any time, should the automated system fail. The current research compared and contrasted the driver's experience when operating a vehicle under Level-2 automation with that of operating the same vehicle when automation was not engaged.

Our research assessed driver workload and visual engagement using electroencephalography (EEG). EEG is the measurement of the summated electrical activity of the brain, recorded non-invasively from electrodes on the scalp. EEG provides high temporal resolution (within milliseconds) and therefore a direct record of neural activity in real-time [11]. Oscillatory components of EEG can be decomposed into canonical spectral frequencies (e.g., Delta ~0.5-4 Hz, Theta ~4-8 Hz, Alpha ~8-12 Hz, and Beta ~12-30 Hz) using Fourier analysis [4]. These frequency bands have been studied in relation to various neurocognitive functions. For example, theta frequency in the frontal regions of the brain is studied as an index of cognitive workload, such that theta power increases with driving demand [5,6] and with cognitive fatigue [9]. Meanwhile, alpha power in the parietal regions of the brain has also been studied in relation to selective visual attention, such that higher alpha power indicates lower visual engagement with the environment and lower alpha power indicates higher visual engagement [2]. Parietal alpha power is highest when an individual's eyes are closed [7]. Therefore, measuring power in the theta and alpha bands can be used to assess changes in workload and visual engagement while driving, respectively. In the current study, we utilized a mobile EEG system to measure frontal theta and parietal alpha while driving.

We performed an on-road evaluation of drivers between the ages of 21-64 operating up to four different vehicles that supported Level-2 automation on both urban and rural roadways. The research design was 4 (Vehicle: Cadillac CT6, Nissan Rogue,

Tesla Model 3, Volvo XC90) x 2 (Age: 21-42 vs. 43-64) x 2 (Automation: Level-0 vs. Level-2) x 2 (Interstate: I-80 vs. I-15) factorial with 24 younger and 24 older participants tested in each of the vehicles. Since most participants were new to this technology, they first completed an extensive training protocol on the automated features of the vehicle. Data collection began with four minutes of eyes-closed EEG recording to get a baseline level of parietal alpha power. Participants then drove two different routes while EEG data were recorded. One route, I-80, was a low trafficked, curvy interstate highway. The other route, I-15, was a heavily trafficked, straight interstate highway. On each highway, participants drove with Level-2 partial automation features engaged or not engaged (in a counterbalanced order) for approximately 20 minutes each. The total time required to train and test a participant in one of the vehicles was approximately 5 hours.

We hypothesized that if partial automation decreases driver workload and attention as some fear, there would be a decrease in frontal theta power and an increase in parietal alpha power in partially automated compared to manual driving. By contrast, if partial automation increases driver engagement and attention as the technology intends, we would expect to see an increase in frontal theta power and a decrease in parietal alpha power in partially automated compared to manual driving.

Data were analyzed using linear mixed effects models in R [13] to account for the repeated-measures design and any missing data. Models were run using the lme4 package [1]. The repeated subjects factor was input into each model as a random intercept with the other factors of interest (Level of Automation, Interstate, Age, Vehicle) alternately entered as fixed effects. For significant effects, effect sizes were calculated as Cohen's *d*. For null effects, we calculated a Bayes Factor for linear mixed models to determine the strength of the evidence for the null hypothesis over the alternative hypothesis [9].

Collapsed across age cohorts, highways, and vehicles, there was no significant difference in frontal theta power (Level-0: M=3.45, SD=2.12; Level-2: M=3.51, SD=3.08) or parietal alpha power (Level-0: M=2.39, SD=1.59; Level-2: M=2.28, SD=1.62) between manual driving and partially automated driving. This implies that for drivers new to this technology, there was no difference in workload or visual engagement associated with manual versus partially automated driving. There was, however, significantly lower parietal alpha power when driving on the more rural, curvy highway compared to the relatively urban, straight highway (I-15: M=2.42, SD=1.75; I-80: M=2.26, SD=1.45; $\chi^2(1)=7.89$, p=0.005), consistent with expectation that the curvy highway demanded more visual attention. There was no significant difference in frontal theta power (Young: M=3.46, SD=2.10; Old: M=3.50, SD=3.10) or parietal alpha power (Young: M=1.98, SD=1.03; Old: M=2.72, SD=1.98) when controlling for age cohort differences. Lastly, there were no omnibus effects of vehicle on either frontal theta power or parietal alpha power, yet there were slight differences between individual vehicles. The interpretation of between-vehicle differences is beyond the scope of this research project.

The purpose of this study was to compare the driver's experience under partial automation and manual driving conditions using EEG. Even though some argue that automation's intention to mitigate distraction and inattention may in fact lead to under-arousal and disengagement from the environment, our data suggest that driving a partially automated vehicle does not, in fact, significantly alter mental workload or visual engagement, particularly for drivers new to the technology. The data establish that participants remained engaged with the driving task when partial automation was enabled. This pattern of data meets the SAE guidelines for maintaining awareness during partial automation.

These findings provide an initial understanding of the effect of automation on workload and visual engagement on a neural level when using this vehicle technology for the first time. They extend the research beyond simple behavioral studies on driver behavior and provide insight into neurophysiological responses when drivers operate a vehicle under partial automation. Our study refines a methodology that can be used alongside behavioral measures to assess the driver's experience under partial automation [11].

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References:

[1] Bates, D., Mächler, M., Bolker, B., & Walker, S. (2015). Fitting Linear Mixed-Effects Models Using lme4. *Journal of Statistical Software, 67*(1), 1 - 48.

[2] Bowman, A. D., Griffis, J. C., Visscher, K. M., Dobbins, A. C., Gawne, T. J., DiFrancesco, M. W., & Szaflarski, J. P. (2017). Relationship between alpha rhythm and the default mode network: an EEG-fMRI study. *Journal of Clinical Neurophysiology, 34*(6), 527-533.

[3] Chuang, C. H., Cao, Z., King, J. T., Wu, B. S., Wang, Y. K., & Lin, C. T. (2018). Brain electrodynamic and hemodynamic signatures against fatigue during driving. Frontiers in neuroscience, 12, 181.

[4] Cohen, M. X. (2014). Analyzing neural time series data: theory and practice. MIT press.

[5] Fairclough, S. H., Venables, L., & Tattersall, A. (2005). The influence of task demand and learning on the psychophysiological response. *International Journal of Psychophysiology, 56*(2), 171-184.

[6] Gevins, A., & Smith, M. E. (2003). Neurophysiological measures of cognitive workload during human-computer interaction. *Theoretical Issues in Ergonomics Science, 4*(1-2), 113-131.

[7] Goldman, R. I., Stern, J. M., Engel Jr, J., & Cohen, M. S. (2002). Simultaneous EEG and fMRI of the alpha rhythm. Neuroreport, 13(18), 2487.

[8] Käthner, I., Wriessnegger, S. C., Müller-Putz, G. R., Kübler, A., & Halder, S. (2014). Effects of mental workload and fatigue on the P300, alpha and theta band power during operation of an ERP (P300) brain-computer interface. Biological psychology, 102, 118-129.

[9]Kruschke, J. K. (2011). Bayesian assessment of null values via parameter estimation and model comparison. *Perspectives on Psychological Science, 6*(3), 299-312.

[10]Lal, S. K., & Craig, A. (2002). Driver fatigue: electroencephalography and psychological assessment. *Psychophysiology, 39*(3), 313-321.

[11] Lohani, M., Payne, B. R., & Strayer, D. L. (2019). A review of psychophysiological measures to assess cognitive states in real-world driving. Frontiers in human neuroscience, 13.

[12] Mun, S., Whang, M., Park, S., & Park, M.C. (2017). Effects of mental workload on involuntary attention: A somatosensory ERP study. *Neuropsychologia, 106,* 7–20.

[13] R Core Team (2019). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. Retrieved from https://www.R-project.org/.

[14] SAE (2016). Taxonomy and definitions for terms related to driving automation systems for on-road motor vehicles (Surface Vehicle Recommended Practice: Superseding J3016 Jan 2014), SAE International. Retrieved from https://www.sae.org/standards/content/j3016_201806/

Which impacts of the Hands OFF modality on drivers disconnection for Level 2 Automation Systems Driving?

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Keywords: Autonomous Driving, level 2 automation, Disconnected Driver, attention, driver Monitoring, Hands Off

Context and objective : The level 2 automation system was defined by the SAE [1] as a “partial automation”, that is to say a “driving mode-specific execution by one or more driver assistance systems of both steering and acceleration/deceleration using information about the driving environment, and with the expectation that the human driver completes the OEDR (object and Event Detection Responses) and supervises the driving automation system”. This definition assumes an attentive driver supervising the adequacy between the behavior of the automated system and the different situations encountered while driving. This constraint is also known as driving "Eyes On" and covers different man-machine interaction strategies tending to ensure this attentional implication. Indeed, the question of attention/distraction is crucial for the proper functioning of this type of system. However, we know that maintaining sustained attention with low levels of stimulation puts cognitive skills at risk [2],[3]. This is a major issue in the context of the different regulations existing all over the world. Namely, the Hands-Off system is not currently allowed in Europe which regulates only "Hands On" systems at level 2, while in USA or Japan, the same Hands Off system is currently allowed for marketing. Thus, the objective of this study is to bring some empirical results and theoretical interpretations for positioning this subject in terms of ergonomic and human factors risks and benefits. We compare three possible Driver-Vehicle-Interactions conditions:

1. "Hands On" system: a level 2 system with the obligation for the driver to keep one hand on the steering wheel.
2. “Hands Off”: the same level 2 system, but without the necessity for the driver to keep one hand on the steering wheel.

3. the “Hands OFF EyeMo”: the same as the “hands Off” system but with an Eyes tracker MOnitoring able to alert the driver in case of a glance “off the road” longer than 5 seconds.

Methodology: This experimentation was conducted on two equivalent Dynamic Driving Simulators at RSA and PSA sites. We developed three events, intervening after 20mn of autonomous driving, to test the impacts of the three conditions:

Event 1 (EV1): incidental loss of assistance in a high-speed turn (regulated at 130 km/h): This loss of assistance occurred in a normal Motorway bend (900 m radius). It was implemented as a “silent failure” (the absence of an audible alert is proposed, because of the state of the art, to limit the impact of false alerts). However, changes in the dashboard indicates the deactivation with the disappearance of the Autonomous Driving symbol, as well as a torque of the steering wheel and a suspension of acceleration. The comparison focused on the differences of behavior, measured in terms of maximum lateral offset.

Event 2 (EV2): sudden stop of assistance followed by an obstacle on the roadway: The scenario begins with a truck traveling at 110 km/h in front of the ego car; it moves to the left, leaving visible another truck stopped in the middle of the road (with a traffic cone ahead) and requiring braking or lane changing. A vehicle, travelling about 50 meters back, is positioned in the left lane. The speed of this vehicle was enslaved to the Ego vehicle in order to allow it to change the lane. A beep-sound is associated with the loss of assistance about 300 m from the obstacle. Also, changes in the dashboard indicates the deactivation. There were about 8sec left for the driver to react before the obstacle (commonly used base-lines for this type of scenario [4]). The comparison focused on the differences of behavior measured in terms of minimum time at the lane change obstacle (MTHW) and maximum lateral acceleration. For this event we did not implement on the simulator an additional security ADAS, such as Automatic Emergency Braking, because the implemented failure affected radar and devices involved in target calculation including FCW and AEB.

Event 3 (EV3) was an untimely rotation of the steering wheel occurring in a straight line at low speed (50km/h): The untimely deactivation occurred on a highway bridge where only the left lane was available, road works blocking the right lane. The event was materialized by a rapid movement of the steering wheel to the left that simulates a strong lateral gust of wind, an irregularity of the roadway or a system malfunction. The chosen area was an overpass (which made the Wind effect likely) without Emergency lane on the left to create psychological pressure at low speeds. The comparison focuses on the correction performance measured in terms of maximum lateral deporting before lane correction.

For the all the conditions and events, the subjects' perceptions and feelings were questioned during *an interview* [5] occurring right after each critical event. The interviews were transcribed and analyzed with 6 thematic categories.

Also for the three conditions of driving, an *eyes tracker* system recorded the gazes of the drivers.

Population: A total of 120 subjects were recruited by PSA and Renault, with an average of 40 years old (EC-10 years) with 20% of women. A majority of subjects declared to be very interested in ADAS , 20% of the subjects said to be moderately interested. None of the subjects recruited were engaged in professional activity related to the ADAS tested.

Main Results: The results, for the three events tested, showed a significative decrease in driving controllability due to the "hands off" condition. This decrease in performance resulted fore examples in:

- higher trajectory deviations with hands off (EV1 mean lateral offset Hon=1,53 m ; Hoff= 3,33 m ; HoffEyeMo= 2,24 m ; Anova p value < 0,01**), (EV3 mean lateral offset Hon: 0,88 m, ; Hoff: 1,43 m ; HoffEyeMo 1,78 m ; Anova p value < 0,001***),

In terms of loss of controllability (crash risk), by considering deviations ratio of more than 0.8 m inside the adjacent lane, we got 14% with Hon condition ; 60% in case oh Hoff and 42 % with HoffEyMo.

- shortened obstacle times with hands off (Ev2 mean Minimum Time HeadWay Hon=3,1s ; Hoff=2,4s; HoffEyeMo=2,4s , Anova p value < 0,05*).

In terms of controllability, by considering MTHW ratio of less than 1second we got 0% with Hon; 19% in case of Hoff and 12 % with HoffEyMo.

- We can say that the hands OFF EyeMo condition, with monitoring of the gaze 5sec, does not restore the driving performance to reach the Hands ON condition performance.

We develop explanatory dimensions of these results. Observations and interviews indicate that in the hands OFF condition, drivers:

1. Watch less the road and have more NDA (Not Driving Activities);
2. Feel less vigilant, are more prone to boredom (those who do not have NDA);
3. Feel more disconnected from driving, have less awareness of the system state and of the traffic around, with less anticipation of what the system will (or not) do;

We assume that the contact of the steering wheel plays an important role in these phenomena and will develop this point.

We noted that he Hands OFF EyeMo condition, with monitoring of the gaze, does not restore the driving performance to reach the Hands ON condition performance. Indeed, if monitoring does generate a gaze back on the road, this gaze would not be associated with much vigilance and attention, as if they looked but not saw. Moreover, the cognitive and bodily disconnections, described in Hands OFF condition, does not seem improved with the monitoring. It can explain why the performance in Hands OFF EyeMo is closer to those observed in Hands OFF than in Hands ON conditions.

Finally, concerning the perceptions of the systems tested, we note that in Hands OFF condition, the subjects feel more like “a passenger”, free, relaxed, but also less responsible; they a priori attribute, wrongly, more capacity to the system than in Hands ON condition. The question of where to place ones hands were also raised. Conversely, hands ON, the physical contact with the moving steering wheel is often considered as unpleasant, even if useful. In Hands off EyeMo, visual monitoring is perceived as constraining but essential.

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References:

[1] SAE international: Taxonomy and Definitions for Terms Related to Driving Automation Systems for On-Road Motor Vehicles. 2016 J3016

[2] Molloy, R., Parasuraman, R.: Monitoring an Automated System for a Single Failure:

Vigilance and Task Complexity Effects . HUMAN FACTORS, 1996,38(2), pp. 311-322
[3] Bainbridge, L.: Ironies of automation. Automatica, 1983, 19(6), 775–779.
[4] Gold, C., Damböck D., Lorenz L., Bengler K.: C. L. (2013). "Take over!" How long does it take to get the driver back into the loop? Proceedings of the Human Factors and Ergonomics Society Annual Meeting 2013 57: 1938
[5] Cahour, B., Salembier P., Zouinar M.: Analysing lived experience of activity, Le travail humain (Human Work), 2016. 3-79, p.259-284

How far smartphone activities are easily interruptible during HAD? A pilot study

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Introduction

Highly automated systems for automotive is going to offer free time to drivers. As several studies recently described it, drivers will prefer to engage in another activity while delegating control to the system than supervising it (Dingus et al., 2006; Large et al., 2020). One of the more common activity categories reported by the latest studies is the use of electronic devices, tablet or smartphones, to text, to watch videos, to navigate or to play (Clark et al., 2017; Hecht et al., 2020; Olson et al., 2009). In the context of individual cars, Hecht et al. found that general use of smartphone and texting are the most attractive activities according to their online survey (2020). The use of smartphone and the wide variety of activities that it offers give a large field to explore. So, the driver will very often engage in a Non-Driving-Related-Task (NDRT). What would be the impact on his capacity to regain vehicle control when it will be necessary? In fact, transitions between driver and the system are going to be more and more common because of the emergence and democratisation of highly automated driving systems but also because fully automated vehicle, able to drive in all situations seems to be still far in the future. The driver's ability, when engaged in NDRT, to manage control transitions is a crucial question. How different will be the reactions depending on the activity of the driver before the transition (Marberger et al., 2018; Mouloua & Hancock, 2019; Park et al., 2019; Richards & Stedmon, 2016). Some previous studies used interruption theory to explore this issue (Befelein et al., 2018) and combined it with different on-board behavior variables (Wandtner, Schmidt, et al., 2018; Wandtner, Schömig, et al., 2018) to investigate the NDRT engagement variations and its impact on driving performance. These approaches are commonly based on multitasking models (Ho et al., 2001, 2004; Salvucci et al., 2009) which attempt to explain switching mechanisms between different tasks. Sequences of actions are explored through cognitive mechanisms. These approaches give clues to investigate multitasking situations, as a takeover situation to handle after a phase of automation: stopping the current activity and re-engaging in the driving task in a very short period.

Objectives

This online study was conducted in April 2020 as a pilot study to explore differences between popular activities through declared levels of interruption. 340 participants took part in the study. NDRTs (Video vs. Reading vs. Playing) and motivation (Insistent instruction vs. No particular instruction) were used as independent variables.

Experimental design

The online study was conducted through a google form. The title of the study was “Automatisation et Cognition”. The link to the study was sent through different ways (social media, university channels and sports communities). It contains three activities chosen in function of previous research on NDRT occurrence during highly automated phases (Large et al., 2020; Olson et al., 2009). Each participant did each activity in the same order as presented below. The first activity was a compilation of short videos extracted from a well-known scientific cartoon for adults. The video approximately lasted 3 minutes. The second activity was a news article about the different shapes and colours of the moon during a year. It was calculated that the reading took in average 4 minutes. The last activity was the mental rotation game. Twelve items were extracted from an official standardized rotation mental test (Vandenberg & Kuse, 1978). The instruction for each item was to find among 4 figures which one is the equal to the one presented at first but in a different position (see figure 1). The three others were distractors. This last activity lasted on average 5 minutes. after each activity, the participants were asked to imagine themselves doing it but in a HAD vehicle launched in an automated mode. Then, three questions were asked about the perceived interruption level of the activity. For each question, it was described how the interruption would appear:

- The system communicates a navigation information by an auditory message (case 1).
- The system communicates a navigation information by a beep and a visual information through a pop-up on the central screen of the cockpit (case 2).
- The system communicates a navigation information only by a visual pop-up on the central screen of the cockpit (case 3).

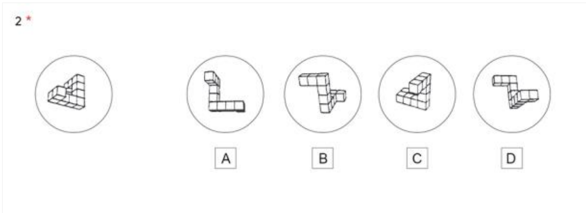

Figure 1 - Example of the mental rotation game item

To ensure that it was clearly understood and to make it more vivid, a video which described and illustrated the different cases was displayed. A 5-items-lickert-scale from “Not at all” to “Extremely” was used to collect the disturbing level of the communication presented. This design to measure how much the participants felt disturbed by the alert was inspired from previous research (Fogarty et al., 2005; Kern & Schiele, 2006). So, an interruption score was calculated for each activity but also for each system communication type.

Results

First, a global score of the perceived disruption was calculated for each task by combining the three answers obtained for each of them. Significant differences on disrupting ratings for the question “How disturbing was the system intervention?” were found between watching a video ($t(326)=57.3$, $p<001$), reading an article ($t(326)=55,8$, $p<.001$) and doing a mental rotation exercise ($t(326)=43.2$, $p<001$). As illustrated in figure 2, reading was the less interruptible activity (high rating of disruption associated to a task means that the task is not easily interruptible) while the video was associated to less disruption.

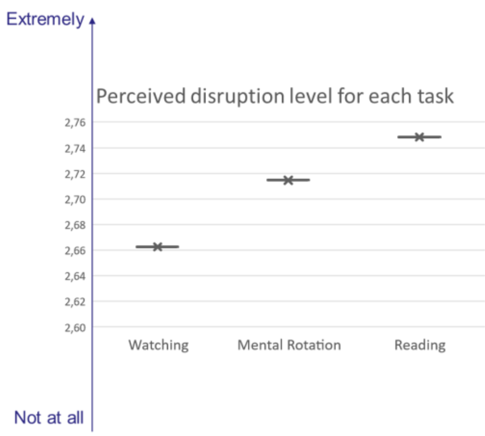

Figure 2 - Interruption ratings in function of activity

More precisely, Figure 3 showed that the ratings of case 1 (the system communicates a navigation information by an auditory message) is the point that make the difference between the video and the reading. Indeed, ratings for the case 1 are more concentrated in the high part of the scale than for the video. It probably means that receiving a vocal information while reading is particularly discordant, more than while watching a video. Moreover, results showed more dispersion in the ratings for the video game: participants feelings about the interruption of a video game are more heterogenous.

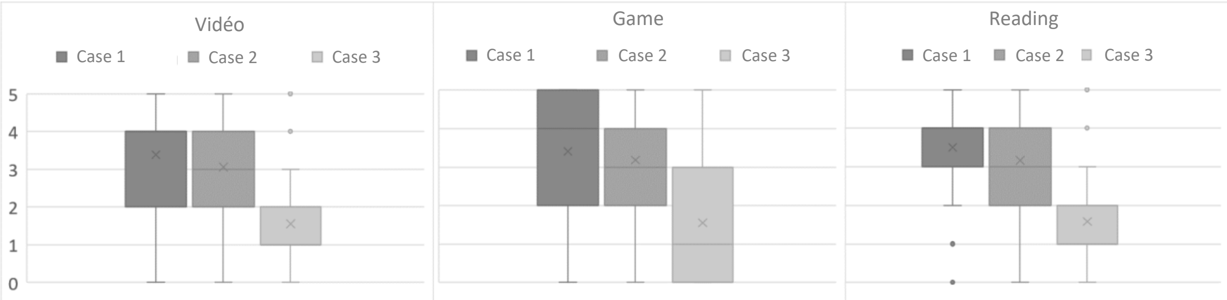

Figure 3 - Disruption ratings in function of the notification and the activity type.

Conclusion

Through our online study, we observed that the way to receive a system communication during an activity seems to have an effect on the perceived level of disruption. These results are particularly consistent with the Multiple Resource Theory (Wickens, 2002) which predict greater interferences between two tasks that use two distinct modalities (here visual and auditory). The attributed interruption level also appeared different in function of the type of activity. The activity of reading appeared to be the less interruptible while the video watching was the most interruptible. These rating differences between each task were highly significant. Through future research works, it would be interesting to explore the effect of the type of activity on a driver behaviour in the context on highly automated driving.

Références

Befelein, D., Boschet, J., & Neukum, A. (2018). Influence of non-driving-related tasks' motivational aspects and interruption effort on driver take-over performance in conditionally automated driving. *6th international conference on driver distraction and inattention, Gothenburg, Sweden. Retrieved from: http://ddi2018. org/wp-content/uploads/2018/10 S, 9*.

Clark, H., McLaughlin, A. C., Williams, B., & Feng, J. (2017). Performance in Takeover and Characteristics of Non-driving Related Tasks during Highly Automated Driving in Younger and Older Drivers. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, *61*(1), 37-41. https://doi.org/10.1177/1541931213601504

Dingus, T., Klauer, S., Lewis, V., Petersen, A., Lee, S., Sudweeks, J., Perez, M., Hankey, J., Ramsey, D., Gupta, S., Bucher, C., Doerzaph, Z., Jermeland, J., & Knipling, R. (2006). *The 100-Car Naturalistic Driving Study : Phase II – Results of the 100-Car Field Experiment*.

Fogarty, J., Hudson, S. E., Atkeson, C. G., Avrahami, D., Forlizzi, J., Kiesler, S., Lee, J. C., & Yang, J. (2005). Predicting human interruptibility with sensors. *ACM Transactions on Computer-Human Interaction (TOCHI)*, *12*(1), 119-146.

Hecht, T., Darlagiannis, E., & Bengler, K. (2020). Non-driving Related Activities in Automated Driving – An Online Survey Investigating User Needs. In T. Ahram, W. Karwowski, S. Pickl, & R. Taiar (Éds.), *Human Systems Engineering and Design II* (p. 182-188). Springer International Publishing. https://doi.org/10.1007/978-3-030-27928-8_28

Ho, C.-Y., Nikolic, M. I., & Sarter, N. B. (2001). Supporting Timesharing and Interruption Management Through Multimodal Information Presentation. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, *45*(4), 341-345. https://doi.org/10.1177/154193120104500416

Ho, C.-Y., Nikolic, M. I., Waters, M. J., & Sarter, N. B. (2004). Not Now ! Supporting Interruption Management by Indicating the Modality and Urgency of Pending Tasks. *Human Factors*, *46*(3), 399-409. https://doi.org/10.1518/hfes.46.3.399.50397

Kern, N., & Schiele, B. (2006). Towards personalized mobile interruptibility estimation. *International Symposium on Location-and Context-Awareness*, 134-150.

Large, D., Shaw, E., & Burnett, G. (2020). *Towards Future Driver Training : Analysing Human Behaviour in Level 3 Automated Cars*. https://nottingham-repository.worktribe.com/output/3811742/towards-future-driver-training-analysing-human-behaviour-in-level-3-automated-cars

Marberger, C., Mielenz, H., Naujoks, F., Radlmayr, J., Bengler, K., & Wandtner, B. (2018). Understanding and Applying the Concept of "Driver Availability" in Automated Driving. In N. A. Stanton (Éd.), *Advances in Human Aspects of Transportation* (Vol. 597, p. 595-605). Springer International Publishing. https://doi.org/10.1007/978-3-319-60441-1_58

Mouloua, M., & Hancock, P. A. (2019). *Human Performance in Automated and Autonomous Systems : Current Theory and Methods*. CRC Press.

Olson, R. L., Hanowski, R. J., Hickman, J. S., & Bocanegra, J. L. (2009). *Driver Distraction in Commercial Vehicle Operations*. https://trid.trb.org/view/907078

Park, J., Jung, E. S., & Im, Y. (2019). 2H1-6 The Effect of Driver Engagement in Autonomous Driving based on Flow Experience. *The Japanese Journal of Ergonomics*, *55*(Supplement), 2H1-6-2H1-6. https://doi.org/10.5100/jje.55.2H1-6

Richards, D., & Stedmon, A. (2016). To delegate or not to delegate : A review of control frameworks for autonomous cars. *Applied Ergonomics*, *53*, 383-388. https://doi.org/10.1016/j.apergo.2015.10.011

Salvucci, D. D., Taatgen, N. A., & Borst, J. P. (2009). *Toward a Unified Theory of the Multitasking Continuum : From Concurrent Performance to Task Switching, Interruption, and Resumption*. 10.

Vandenberg, S. G., & Kuse, A. R. (1978). Mental Rotations, a Group Test of Three-Dimensional Spatial Visualization. *Perceptual and Motor Skills*, *47*(2), 599-604. https://doi.org/10.2466/pms.1978.47.2.599

Wandtner, B., Schmidt, G., Schoemig, N., & Kunde, W. (2018). Non-driving related tasks in highly automated driving—Effects of task modalities and cognitive workload on take-over performance. *AmE 2018 - Automotive meets Electronics; 9th GMM-Symposium*, 1-6.

Wandtner, B., Schömig, N., & Schmidt, G. (2018). Effects of Non-Driving Related Task Modalities on Takeover Performance in Highly Automated Driving. *Human Factors*, *60*(6), 870-881. https://doi.org/10.1177/0018720818768199

Wickens, C. D. (2002). Multiple resources and performance prediction. *Theoretical issues in ergonomics science*, *3*(2), 159-177.

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Characterisation of Visual Distractions in Drivers Associated with Accident Risk: A Multi-Component Investigation

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Keywords: accidents, distraction, drivers, simulator, visual task

ABSTRACT

This paper outlines and activity to characterise visual distractions in drivers associated with accident risk. An approach involving multiple research activities is employed to investigate relevant parameters and identify objective components of high-risk visual distractions.

Background:
Short visual distractions involve secondary tasks engaging driver's visual attention away from the primary driving task, and are known to be an underlying cause in a significant number of road accidents and near misses [1]. These reduce driver capability for effective response to the road environment and closely relate to errors leading to outcomes with a high accident risk [2]. Given their prevalence, risks associated with visual distraction are a key focus in road safety.

Implementation of assistance systems able to detect and respond to driver visual distractions is a key mitigation strategy to accident risk. Active visual distraction monitoring systems work to classify driver behaviour according the type and associated risk [3]. This determination triggers appropriate response to effectively mitigate and/or prevent driver engagement in secondary tasks, with successful execution depending on defined parameters of visual distraction for use as criteria in distraction state determination [4].

Much investigation has been conducted into classification of tasks contributing to visual distraction in drivers and is widely reported [5]. Objective parameters that may be used in the classification of visual distractions and their associated are less defined. For this it is important to characterise visual distractions by objective criteria and to define how each of these relate to the relative risk of accidents under relevant road scenarios.

Aims:
The objective of the study is to investigate and assess driver visual attention associated with road traffic accidents and near-misses. This aims to characterise short visual distractions acting as contributing factors in such scenarios under objective criteria, and according to related risk.

Driver visual distraction characterisation involves investigation and validation of behaviours associated with a high risk outcome. These are defined with respect to the following criteria:

- Classification of distraction type (i.e. smartphone use, infotainment use, other)
- Visual behaviour (fixations or glances) period and speed between driving and non-driving related targets
- Degree of eye and head movement between targets associated with the driving task and those associated with a secondary task (task target relative position).
- Frequency of visual attention changes between the driving task and a secondary task

Methodology:
The study takes a multi-stage approach to investigation of driver distractions and the associated risk of road accidents. Initial stage investigation involves two parallel activities. The first evaluates critical scenarios associated with visual distraction, with the second assessing driver visual distraction by general task and objective components. Project activities culminate in a naïve driver simulator study.

Critical scenarios are assessed by means of a literature based accidentology study and supporting complemented by accident database data. Outcomes identify representative scenarios relevant to high frequency of occurrence and a higher outcome severity, which are implemented in a virtual environment for driving simulator evaluations.

Visual distraction is defined with the aim of forming a taxonomy of visual distraction behaviours in drivers. It was conducted by an examination of existing literature around visual distraction characteristics and associated secondary tasks, and a naturalistic field study involving 12 volunteer drivers with eye tracking sensors and interior cameras fitted to their vehicle. This recorded visual behaviour and interactions when engaging with secondary tasks. Outcomes are used in definition of representative driver distraction inducements.

The subsequent dynamic driving simulator experiment involved 126 naïve driver participants. 12 conditions were tested, with 4 visual task inducements representative of identified distraction characteristics and 3 identified critical scenarios. Drivers were instructed to engage in one inducement task at multiple defined points whilst driving in the simulated environment. During distraction inducement each of the critical scenarios were presented to them. Data is collected regarding scenario outcome, driver state of visual attention, the driver reaction, and driver perception of the scenario severity and task difficulty.

Analysis of simulator testing assesses outcomes and determines risk associated with each induced distraction and critical event. Meta-analysis follows, relating recorded outcomes of tested simulator conditions, to defined characteristics of distraction and quantify risks. This identifies the associated risk according to objective parameters of distraction.

Results:
The initial accidentology study consulted 42 resources which defined scenarios associated with visual distraction, with 24 of these reviewed in detail. Outcomes from 14 sources were used for scenario definition input, made up of a combination of survey-based studies and the outcomes of targeted accident database analysis. The literature investigation was complemented by accident data coming from GIDAS (German In-Depth Accident Study) dataset. Accidents were considered where the guilty participant was a passenger car and was distracted and involved a total of 21317 accidents. The accidentology outcomes identified rear end, and single vehicle accidents as being the most prevalent and high-risk scenarios associated with visual distractions. Second to these were crossing scenarios. Specific representative

parameters for each of these were also identified from the reviewed resources. Based upon the analysis of prevalence and risk, one of each of these critical events was represented as part of developed scenarios for simulator testing.

The evaluation resources for driver visual distractions consulted 50 resources, of which 24 were analysed in detail. These report survey-based studies, accident data analysis, and real-world driving studies. Output from sources mainly identifies secondary tasks with regards to their classification, with use of use of mobile phones, interaction with other vehicle occupants, and use of non-driving related vehicle systems being the most prevalent. These findings were also supported by subjective analysis of the real-world driving study data. Evidence was found for more specific parameters of visual behaviour within both literature and field test outcomes. This outlined a distinction between “timesharing” and “fixation” behaviour, alongside association of distraction visual target position relative to the forward view. Four representative visual distraction inducement tasks were defined based upon outcomes. These were based upon position relative to the forward view, and the type of visual interaction (fixation or timeshare).

Simulator study experiment results show differences in the effect of different distraction inducements on the outcomes of critical scenarios, and the associated risk. Analysis of outcomes shows differences in prevalence of severe outcomes (collision, no collision, control loss), severity of each outcome (speed profile), and the effective driver reaction (reaction time and manoeuvre) according to the inducement. Across all of the 3 testes scenarios analysis shows that fixation tasks are associated with an overall increase in severe outcomes, higher risk during those outcomes, and later driver reactions relative to corresponding timesharing tasks. Position of the visual task target sees general trends in the data towards higher risk outcomes for task targets positioned further away from the forward view, both vertically and laterally. For some event and inducement combinations where the task location is more approximate to the position of critical stimuli in the simulated environment, this trend was lessened.

Conclusions:
Results from the simulator study, coupled with the findings of previous project phases provide evidence to allow for characterisation of visual distraction in drivers according to the outlined criteria. Evidence is also found to validate the probability of severe outcomes and relative risk for each. The activities were not fully successful in quantifying the speed of visual glance behaviour between driving and non-driving related targets and associated degree of risk.

References:

[1] Bálint, A., Flannagan, C. A., Leslie, A., Klauer, S., Guo, F., Dozza, M., Multitasking additional-to-driving: Prevalence, structure, and associated risk in SHRP2 naturalistic driving data. Accident Analysis & Prevention, 2020, 137, pp. 105–115
[2] Young, K.L., Salmon, P.M., Examining the relationship between driver distraction and driving errors: A discussion of theory, studies and methods, Safety science, 2012, 50, (2), pp. 165-174
[3] Kang, H.B., Various approaches for driver and driving behavior monitoring: A review. In Proceedings of the IEEE International Conference on Computer Vision Workshops, 2013, pp. 616-623
[4] Fernández, A., Usamentiaga, R., Carús, J. L., Casado, R., Driver distraction using visual-based sensors and algorithms. Sensors, 2016, 16, (11), pp. 1805
[5] Qin, L., Li, Z. R., Chen, Z., Bill, M. A., Noyce, D. A.,. Understanding driver distractions in fatal crashes: An exploratory empirical analysis. Journal of safety research, 2019, 69, pp. 23-31.

Vehicle Control and Response to Emerging Events: It's Both Off-Road and On-Road Glance Duration

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Keywords: Attention, driver distraction, long glances, situation awareness

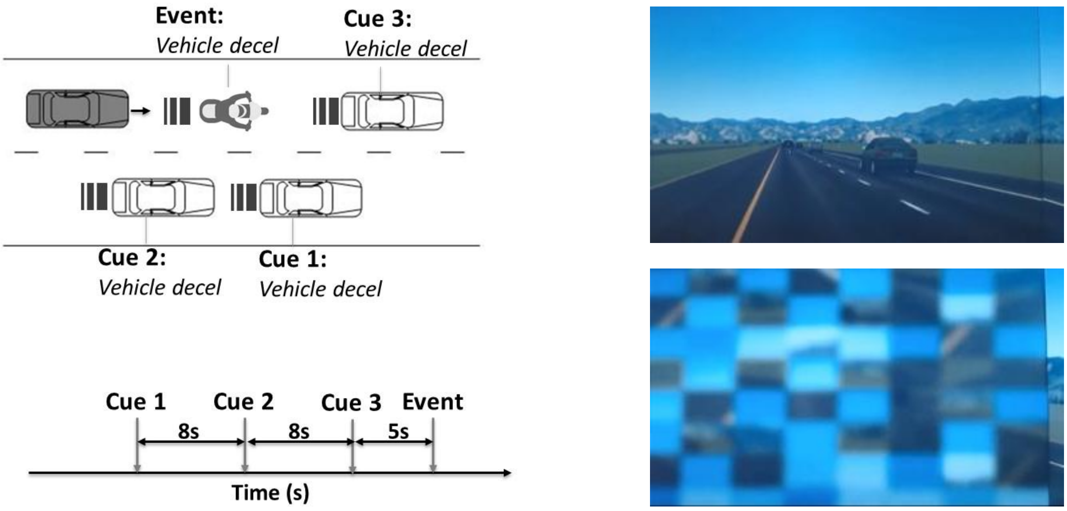
ABSTRACT

It is well established that long off-road glances increase the risk of crashes (e.g. [1]). When drivers look away from the road to perform a task, it depletes their situation awareness (SA). SA can be defined as the knowledge of what's around the vehicle, how objects are moving, and whether collision potential is increasing. While minimizing off-road glances remains critical for safe driving, research also suggests that looking back at the road for more than a brief glance helps rebuild sufficient SA for maintaining stable control and for recognition of unfolding conflicts. It's been found that this aspect of attention to the road differentiates crashes from near-crashes [2]. Following Kircher and Ahlström's AttenD model [3], a 2s loss of visual information should critically deplete a driver's awareness of his/her position within the lane. Based on recent scene perception findings, once a driver looks back on-road following an off-road glance, it takes approximately 200ms of on-road viewing to establish basic perception of a scene (or Level 1 SA; [4]). It takes on the order of 500-1500ms to establish Level 2 awareness (i.e., comprehension) such that a driver is appropriately responsive to bottom-up cues that signal a potential impending hazard [4,5]. However, based on preliminary testing from an unpublished image detection study (and from relevant literature; e.g., [6]), it may take more on the order of 4-8s to establish Level 3 awareness (i.e., prediction) of a scene in order to appropriately detect hazards using both bottom-up and top-down cueing. The driving simulator study reported here considered the impact of shorter (2s) and longer (6s) on-road glance intervals between a series of 2s long off-road glance periods.

Participants were experienced drivers between the ages of 20 and 34 or 55 and 69. The MIT AgeLab's upgraded driving simulator (fabricated by Realtime Technologies Inc., Ann Arbor, MI) consists of the full cab of a 2001 Volkswagen New Beetle mounted on a three-degree of freedom motion base. Three exterior projection screens provide an approximate 180-degree forward field of view. Rear views are provided in actual side mirrors and the rear-view mirror. Participants interacted with the simulator through a full-scale automotive steering wheel, throttle, and brake pedal inputs.

The basic driving scenario ran 3 minutes. Participants followed a lead vehicle on a divided highway (2 lanes each direction) and were instructed to follow the speed limit of 65 mph. There were no curves and the road scenery contained only light foliage (Fig. 1). During the last 25s of the scenario, drivers encountered traffic cues predictive of a downstream event (a hard deceleration by the lead vehicle), to which they had to brake to avoid a collision. The set of cues (Fig. 1) were sequenced to occur in the same order and timing for each participant. The vehicle directly in front of the participant was a motorcycle, providing an unobstructed view of the brake lights of the vehicle traveling in front of it. The onset of this vehicle's brake lights (i.e., Cue 3) preceded the Event.

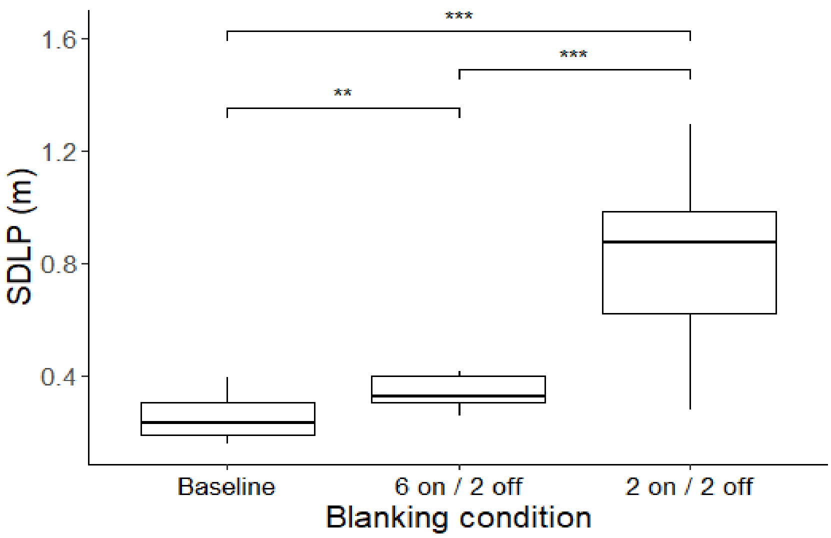
Figure 1. (left) Cue and event sequence and timing. (right) Forward road scene without (top image) and with (bottom image) masking for the 2s blanking periods.



Participants experienced the scenario first without any external constraints on their forward view. This provided an opportunity to orient participants to the importance of attending carefully to forward scene information (as is the case in real-world driving). The drive was repeated a second time with the addition of an artificially-imposed series of masks over the forward scene (blanking; see Fig. 1, lower right) to force the loss of visual information corresponding to a 2s off-road glance. A sequence of 2s "off-road glances" began after one minute of normal driving and a short interval of task instructions. Out of 21 participants in the analysis sample, just over half (N=11) were exposed to 2s-long unmasked forward roadway views between 2s of off-road glance time, while the remainder (N=10) experienced 6s-long unmasked views. Age and gender were closely balanced across the two groups. For the first 95s of the alternating road visible and blanking sequencing, the surrounding traffic continued at a consistent speed matched to the driver's speed. The blanking sequences continued up to the Event onset (for a total of 116s of on and off-road glance sequences). This duration, while seeming long compared to some tasks, is within the range for many visual-manual tasks studied (e.g., navigation destination entry [7], texting [8]).

Staring at a masked road image enforces a SA decrement for experimental purposes, but is clearly not a normal experience. To induce an off-road glance pattern similar to one employed when interacting with a cell-phone or other secondary activity, a visual monitoring task was included. A rectangular device approximately the height and twice the width of a medium sized smartphone was placed in their lap. Single digit numerical displays were located in each corner (up, down, left, right). A tone prompted participants when it was time to look down at the device. This corresponded to the start of a masking period. They were to continue looking at the device until one of the four displays lit-up with a flashing '0' (masking ends). This simultaneous procedure produced the functional experience of physically moving the head and eyes downward to engage in a secondary activity, while masking of the screen ensured that an actual loss of view of the forward road occurred for a full 2s. In addition, physical orientation of the head and eye away from the forward view might be expected to have greater impact on basic vehicle control since drivers tend to steer toward where they are looking [9,10]. Thus, this artificial secondary task modeled the impact that moving the head and eyes off-road, as well as a modest cognitive load [6], which would be missing from occlusion alone.

Figure 2. Standard deviation of lane position (SDLP) for baseline driving and the two blanking conditions (** = $p < .01$; *** = $p < .001$) and crash rates.



As anticipated based on Sender's [11] classic work, 2s off-road glances (occlusion/blanking) significantly impacted basic vehicle control as measured by SDLP ($F(2,39) = 38.00$, $p < .001$). However, while off-road glance durations were 2s long in both blanking conditions, the intervening duration of the restored view of the forward roadway significantly influenced the magnitude of this effect. Interleaving brief 2s on-road views resulted in SDLP values 325% greater than baseline ($t(30) = 7.76$, $p < .001$) (Fig. 2). In contrast, interleaving 6s on-road views resulted in a significant ($t(29) = 3.56$, $p < .01$) but more modest 43% increase over baseline. The difference between 2s and 6s conditions was also significant ($t(19) = 4.358$, $p < .001$). Successful avoidance of a crash during the cueing and brake sequence was considered by blanking condition. While nearly half of the 2s on / 2s off participants crashed into the lead vehicle (5 of 11), only one of the 6s on / 2s off participants did, suggesting that crash risk (to the extent it can be measured in a simulator study) was substantially reduced by increasing the amount of eyes-on-road time between 2s off-road glance periods.

In this driving scenario with sequences of experimentally-induced off-road glancing, the time between off-road glances was a critical factor in differentiating lateral lane maintenance (SDLP) and crash avoidance. While the speed at which good vehicle control and SA is reacquired is likely highly related to individual characteristics and driving context, this study indicated that longer glance time to the road supports refilling of depleted SA reserves. As such, interleaving long on-road glances are advantageous and should be encouraged [2,12,13].

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References:

[1] Klauer, S. G., Dingus, T. A., Neale, V. L., Sudweeks, J. D., & Ramsey, D. J.: "The impact of driver inattention on near-crash/crash risk: An analysis using the 100-car naturalistic driving study data", 2006, US DOT Report HS810594.
[2] Seppelt, B., Seaman, S., Lee, J., Angell, L.S., Mehler, B. & Reimer, B.: "Glass half-full: use of on-road glance metrics to differentiate crashes from near-crashes in the 100-car data", Accident Analysis and Prevention, 2017, 107, pp. 48-62.
[3] Kircher, K., & Ahlström, C.: "Issues related to the driver distraction detection algorithm AttenD", Proc. 1st Inter. Conf. on Driver Distraction & Inattention, 2009, Gothenburg.
[4] Wolfe, B., Fridman, L., Kosovicheva, A., Seppelt, B., Mehler, B., Reimer, B., & Rosenholtz, R.: "Predicting road scenes from brief views of driving video", Journal of Vision, 2019, 19(5), pp. 8-8.
[5] Wolfe, B., Seppelt, B., Mehler, B., Reimer, B., & Rosenholtz, R.: "Rapid holistic perception and evasion of road hazards", Journal of Experimental Psychology: General, 2020, 140(3), pp. 490-500.
[6] Samuel, S., & Fisher, D. L.: "Evaluation of the minimum forward roadway glance duration", Transportation Research Record, 2015, 2518(1), pp. 9-17.
[7] Angell, L., Auflick, J., Austria, P. A., Kochhar, D., Tijerina, L., Biever, W., Diptiman, T., Hogsett, J., & Kiger, S.: "Driver Workload Metrics Task 2 Final Report,", 2006, US DOT Report HS 810635.
[8] McKeever, J.D., Schultheis, M.T., Padmanaban, V., & Blasco, A. "Driver performance while texting: Even a little is too much.", Traffic Injury Prevention, 2018, 14(2), 132-137.
[9] Land, M., & Horwood, J.: "Which parts of the road guide steering?", Nature, 1995, 377(6547), pp. 339-340.
[10] Mole, C., Giles, O., Merat, N., Romano, R., Markkula, G., & Wilkie, R.: "Where you look during automation influences where you steer after take-over." Proc. 10th Inter. Driving Symp. on Hum. Fact. in Driver Assessment, Training, & Vehicle Design, 2019, Santa Fe, New Mexico, USA.
[11] Senders, J. W., Kristofferson, A. B., Levison, W. H., Dietrich, C. W., & Ward, J. L.: "The attentional demand of automobile driving", 1967, pp. 15-33.
[12] Seppelt, B., Seaman, S., Angell, L., Mehler, B. & Reimer, B.: "Assessing the effect of in-vehicle task interactions on attention management in safety-critical events", Proc. 6th Intern. Conf. on Driver Distraction & Inattention, 2018, Gothenburg, Sweden.
[13] Seaman, S., Lee, J., Seppelt, B., Angell, L., Mehler, B., & Reimer, B.: "It's all in the

timing: using the AttenD algorithm to assess texting in the NEST naturalistic driving database", Proc. 9th Inter. Driving Symp. on Hum. Fact. in Driver Assessment, Training, & Vehicle Design, 2017, Manchester Village, Vermont, USA.

A context-dependent multi-buffer driver distraction detection algorithm and its application to automated docking at bus stops

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Keywords: Eye tracking, distraction detection, visual, context, visual time-sharing.

ABSTRACT

Visual driver distraction detection algorithms are typically based on gaze information or lateral and longitudinal driving performance measures [1]. However, with more advanced driving assistance or automated systems, the latter category of vehicle control parameters is no longer useful for driving performance assessment. When it comes to the former category, gaze based visual driver distraction detection, two lines of research have emerged. One branch deals with computer vision and machine learning to extract head pose, gaze direction or secondary task activities from video streams [1-3]. The other branch aims to estimate the attention level of the driver based on the extracted gaze data [4-6]. Unfortunately, there is a gap between these two lines of research. With the recent availability of open source deep learning algorithms and pre-trained networks for facial feature detection and gaze estimation, there has been an upsurge of papers focusing on the image processing problem of visual driver distraction algorithms. However, the branch researching how to go from eye tracking data to a driver attention estimate has practically not evolved in the past decade. This is unfortunate since the breakthroughs made on the image processing side are wasted on simple warning schemes where any secondary task activity or glance away from forward immediately equals distraction.

As a workaround, some visual distraction detection algorithms try to reduce the number of false warnings by measuring the time spent looking away from the forward roadway, see [5, 7] for reviews. The time spent looking away is typically set to around 2 seconds, loosely based on the finding that it is "uncomfortable" to look away for longer times, and also that glances exceeding 2 seconds are considered dangerous [8]. These approaches are better than the "look away from forward immediately equals distraction" strategy in the sense that they take time history into account, meaning that looking away from forward for too often or for too long will eventually result in a distraction warning. A problem is however that they do not consider situation-based attentional requirements at all, or only in a rudimentary way, as

in the AttenD algorithm, which has a built-in mechanism for acknowledging the necessity of mirror and speedometer glances [7].

The objective of this paper is to present a first version of a driver distraction detection algorithm that takes context into account, by extending the AttenD algorithm with elements from the Minimum Required Attention (MiRA) theory [9]. The feasibility of the prototype algorithm has been tested in a simulator experiment investigating automatic docking at bus stops. Sixteen professional bus drivers (age 26 – 62 years, 3 women) drove a route with 10 bus stops in an urban environment, with manual driving and with automated docking, in an alert and a fatigued split shift condition (i.e. four drives per participant). While driving manually between the bus stops, the drivers performed a visual-manual secondary task in 2 of 10 road stretches. The task was framed as a ticketing machine task, requiring 7 taps on a touch screen to complete the task. Only results from this ticketing task, across all conditions, are presented in this abstract.

The original AttenD algorithm uses gaze direction, connected to a 3D-model of the interior of the vehicle, as input. This means that the algorithm knows which objects in the vehicle that the driver looks at (mirrors, windows, speedometer etc.). AttenD is, however, unaware of the surroundings outside the vehicle. A so-called field relevant for driving (FRD) is assumed, which covers the forward region where a cone with 45-degree radius intersects with the windscreen. The driver has a buffer of two seconds, which is decremented when the driver looks outside the FRD. Upon gazing back at the FRD, the buffer is increased over time after a refractory period of 0.1 s. When gazing towards the mirrors or the speedometer, the depletion starts only after a delay of 1 s. When the buffer reaches 0, the driver is assumed to be distracted.

Here, AttenD was extended in three ways. *First*, instead of having one buffer with conditional rules for the mirrors and the speedometer, multiple buffers were generated, one per traffic relevant area. Separate buffers were incorporated for the FRD, the left mirror and the right mirror. The number of buffers was also made situation dependent. Since this project focused on automated versus manual docking at bus stops, a region encompassing the bus stop area was added to the 3D-model. When approaching the bus stop, this region became active and the buffer associated with the bus stop region started to deplete. Similarly, a buffer was added to a hands-on sensor in the steering wheel which was active during manual driving and when handing back control to the driver. Note that both the number of objects and the increment/decay rates are adaptive and differ between situations and object types. *Second*, the decay rate of the buffers now varies with speed. When driving above the speed limit, the buffers decrease faster. Similarly, it is possible to buy time by slowing down. *Third*, the buffers decrease/increase based on a logarithmic function loosely based on Senders' information decay rate formulas [10]. The implementation assumes that the mental model of the surrounding environment remains accurate for a while but then quickly turns more and more inaccurate. For glance targets with slower information decay rate, such as the mirrors in a situation where traffic from behind is less relevant, the buffers remain full for a long while until they eventually dissipate rather quickly.

Results from the ticketing task shows that there were distraction detections in 12.5% of the interactions (2.2% in a matched baseline without secondary task). The corresponding percentages for a different algorithmic approach, counting the number of times that the driver looked away from a 12° road center region for more than 2 seconds, was 95.3% during the task and 50.9% during the matched baseline. Apparently, long glances away from a small road center region are highly indicative of visual-manual secondary tasks, but such algorithms also detect a lot of (false) distraction events in normal driving, e.g. when the road turns or when scanning the periphery. Note that 2 of the extended AttenD distraction detections that occurred during the secondary task (1 during baseline) arose due to neglect of the mirrors. This is the advantage of the multi-buffer approach, i.e. that proper visual time-sharing between different traffic relevant targets can be accounted for. Distraction detections arise not only when looking away from forward but also when neglecting traffic relevant information in other directions.

Future work includes expanding the concept to real-world environments by automatically integrating situational information from the vehicles environmental sensing and from digital maps.

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References:

[1] A. Fernández, R. Usamentiaga, J. Carús, and R. Casado, "Driver distraction using visual-based sensors and algorithms," *Sensors,* vol. 16, no. 11, p. 1805, 2016.

[2] S. Masood, A. Rai, A. Aggarwal, M. N. Doja, and M. Ahmad, "Detecting distraction of drivers using convolutional neural network," *Pattern Recognition Letters,* 2018.

[3] D. Tran, H. M. Do, W. Sheng, H. Bai, and G. Chowdhary, "Real-time detection of distracted driving based on deep learning," *IET Intelligent Transport Systems,* vol. 12, no. 10, pp. 1210-1219, 2018.

[4] C. Ahlstrom, K. Kircher, and A. Kircher, "A gaze-based driver distraction warning system and its effect on visual behavior," *IEEE Transactions on Intelligent Transportation Systems,* vol. 14, no. 2, pp. 965-973, 2013.

[5] J. D. Lee *et al.*, "Detection of driver distraction using vision-based algorithms," in *Proc. 23rd Enhanced Safety Veh. Conf*, 2013.

[6] B. D. Seppelt, S. Seaman, J. Lee, L. S. Angell, B. Mehler, and B. Reimer, "Glass half-full: On-road glance metrics differentiate crashes from near-crashes in the 100-car data," *Accident Analysis & Prevention,* vol. 107, pp. 48-62, 2017.

[7] K. Kircher and C. Ahlstrom, "The driver distraction detection algorithm AttenD," in *Driver distraction and inattention: Advances in research and countermeasures*, M. A. Regan, J. D. Lee, and T. W. Victor, Eds. Surrey, UK: Ashgate, 2013, p. Chapter 2.

[8] H. T. Zwahlen, C. C. Adams, and D. P. DeBals, "Safety aspects of CRT touch panel controls in automobiles," in *Vision in Vehicles II. Second International Conference on Vision in VehiclesApplied Vision AssociationErgonomics SocietyAssociation of Optometrists*, 1988.

[9] K. Kircher and C. Ahlstrom, "Minimum required attention: a human-centered approach to driver inattention," *Human factors,* vol. 59, no. 3, pp. 471-484, 2017.

[10] J. W. Senders, A. Kristofferson, W. Levison, C. Dietrich, and J. Ward, "The attentional demand of automobile driving," *Highway research record,* no. 195, 1967.

Visual occlusion as tool to assess attentional demand and spare capacity

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Keywords: Attentional demand, vision, situational context, occlusion, method.

ABSTRACT

Visual occlusion has been used in various ways to evaluate vision related aspects of driving [1]. Senders et al. [2] did pioneering work in real traffic to assess the visual demands of different traffic environments. Occlusion has also been used to simulate glances to traffic while parked to evaluate in-car technology [3], to simulate distraction while driving on a closed course [4], and to assess the influence of a secondary task in driving situations of varying complexity in a simulator [5]. Here, we compile and discuss findings from a series of four studies in which visual occlusion was used to assess situational demand for visual information and visual spare capacity, that is, the possibility to execute an additional visual task while driving. We also discuss the strengths and weaknesses of visual occlusion as a method in this field of research.

The concept of spare capacity has been forgotten in most popular definitions of driver distraction, which typically equate glances away from traffic with distraction. Harking back to Senders et al.'s [2] work, we used visual occlusion with the ultimate aim to achieve a better understanding about the relationship between situational demand, attention and self-regulation. The key features of the four studies are listed in **Table 1**.

	Study I	Study II	Study III	Study IV
aim	assess situation-based minimum required attention	assess situation-based minimum required attention	assess utility of occlusion distance as measure of event density	assess information decay rate under irrevocable occlusion
study platform	field study with instrumented vehicle	fixed-base simulator	motion-base simulator	linear motion-base simulator
road types	motorway	motorway, rural road, urban road	intersection, suburban, motorway	motorway
occlusion	occlusion goggles	blank-out of forward	unoccluding blanked-	blank-out of screen

apparatus	operated by micro-switch on finger, allowing rudimentary peripheral vision	screen (110°) with micro-switch on finger, allowing some peripheral vision	out scene with lever behind steering wheel, no peripheral vision	
occlusion type	self-paced occlusion onset and duration, default: not occluded	self-paced onset, fixed duration closed (1.0-2.6 s, increment 0.4), default: not occluded	self-paced onset, fixed duration open (0.5 s), default: occluded	system-paced, occlusion irrevocable until crash/ run-off-road
N (valid)	25	30	97	22
reference	Kircher, Kujala & Ahlström, 2019 [6]	Liu, Ahlström, Forsman & Kircher, 2019 [7]	Kujala, Mäkelä, Kotilainen & Tokkonen, 2016 [8]	Kircher, Ahlström, Nylin & Mengist, 2018 [9]

Table 1. Key features of the four occlusion studies.

A key finding emerging from all four studies and corroborating previous research is that drivers possess visual spare capacity to varying degrees, depending on several factors, which we will look into more closely in the following. This conclusion is based on the fact that drivers could occlude their vision without ensuing incidents or collisions.

Environmental circumstances predict the likelihood of visual occlusion (Studies II, III), with features like oncoming traffic or intersections, which are associated with higher prediction uncertainty [10], leading to less frequent and shorter occlusions. In more monotonous environments like motorways, the previous occlusion history is a predictor of future occlusions. Studies I, II and III indicated interindividual differences in occlusion strategies, but this was not associated with driving experience (Study III). The results suggest that drivers are sampling information in such a way that they predict and prepare for the near future. In Study II, the likelihood to occlude was lowest upon approaching an intersection and when still closing the gap to an oncoming vehicle but increased already in the first half of an intersection, or when the oncoming vehicle was still a few metres in front of the driver (Study II). In Study IV, drivers corrected their trajectory under occlusion, based on the information sampled before the occlusion occurred. It could be shown that visual occlusion can help differentiating necessary glances to and away from the forward roadway from unnecessary glances (Study I). Necessary glances away include glances to the mirrors and across the shoulder to check the blind spot, which are not neglected when attempting to maximise occlusion time. Comparing occlusion time with occlusion distance, which also incorporates speed, it was found that less information-dense environments allow longer occlusion distances, with occlusion duration being more constant across situations, reflecting higher speeds in less complicated environments (Study III).

We found the visual occlusion method to be a flexible and relatively objective tool to assess various aspects of self-assessed situational attentional demand and spare capacity. Depending on the research question, system-paced or self-paced occlusion with either fixed or variable duration can be used. Different areas of the visual field can be occluded, for example separating peripheral and foveal vision. Compared to executing an additional task, occlusion does not require a mental focus away from driving, except when an additional task is given during the occluded period [11]. A drawback with the occlusion method is the lack of a given benchmark. There are no concrete criteria that allow a judgement of whether the frequency and duration of occlusions were below or just at capacity, or possibly over. An incident or collision would be a clear indication that the minimum required information was not sampled, but the absence of such occurrences does not guarantee that enough information was sampled for safe driving. With an unoccluded default state, many participants in Study I reported that they had occluded below their maximum capacity, keeping a safety margin. This self-reported assessment is supported by Study IV, where collisions/run-off-roads occurred on average first after twice the time or more as the typical self-paced occlusion duration. Usually the occlusion apparatus is operated by hand or foot, which may require more mental effort than the more natural closing of the eyes. Anecdotical evidence shows, however, that the latter quickly leads to mental fatigue and would not allow the flexibility offered by external occlusion devices.

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References:

[1] T. C. Lansdown, P. C. Burns, and A. M. Parkes, "Perspectives on occlusion and requirements for validation," *Applied Ergonomics,* vol. 35, no. 3, pp. 225-232, 2004.

[2] J. W. Senders, A. B. Kristofferson, W. H. Levison, C. W. Dietrich, and J. L. Ward, "The attentional demand of automobile driving," *Highway Research Record,* vol. 195, pp. 15-33, 1967.

[3] M. Baumann, A. Keinath, J. F. Krems, and K. Bengler, "Evaluation of in-vehicle HMI using occlusion techniques: Experimental results and practical implications," *Applied Ergonomics,* vol. 35, pp. 197-205, 2004.

[4] S. B. Brown, "Effects of haptic and auditory warnings on driver intersection behavior and perception," Master of Science Master's Thesis, Industrial and Systems Engineering, Virginia Polytechnic Institute and State University, Blacksburg, Virginia, 2005.

[5] O. Tsimhoni, "Time-sharing of a visual in-vehicle task while driving: findings from the task occlusion method," The University of Michigan Transportation Research Institute (UMTRI), Ann Arbor, MI, Technical Report UMTRI-2003-13, 2003.

[6] K. Kircher, T. Kujala, and C. Ahlström, "On the difference between necessary and unnecessary glances away from the forward roadway: An occlusion study on the motorway," *Human Factors,* 2019.

[7] Z. Liu, C. Ahlström, Å. Forsman, and K. Kircher, "Attentional Demand as a Function of Contextual Factors in Different Traffic Scenarios," *Human Factors,* 2019.

[8] T. Kujala, J. Mäkelä, I. Kotilainen, and T. Tokkonen, "The attentional demand of automobile driving revisited: Occlusion distance as a function of task-relevant event density in realistic driving scenarios," *Human Factors,* vol. 58, pp. 163-180, 2016.

[9] K. Kircher, C. Ahlstrom, M. Nylin, and A. Mengist, "Tactical steering behaviour under irrevocable visual occlusion," *Transportation Research Part F: Traffic Psychology and Behaviour,* vol. 55, pp. 67-77, 2018.

[10] A. Clark, "Whatever next? Predictive brains, situated agents, and the future of

cognitive science," *Behavioral and Brain Sciences,* vol. 36, no. 3, pp. 181-204, 2013.

[11] S. Samuel and D. L. Fisher, "Evaluation of the minimum forward roadway glance duration critical to latent hazard detection," presented at the Transportation Research Board 94th Annual Meeting, Washington DC, USA, 2015. Available: http://trid.trb.org/view.aspx?id=1337244

Development of a Driver Distraction Safety Rating System for New Vehicles: Report on an Australian Study

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Keywords: driver distraction, human factors, in-vehicle infotainment systems, rating, new car assessment program (NCAP), workload

ABSTRACT

Background

There is converging evidence from around the world that drivers engage regularly in competing activities that are distracting (e.g. Dingus et al., 2016; Young et al., 2019), that distraction significantly increases crash risk (e.g. Dingus et al., 2016; Klauer et al., 2014; Cunningham, Regan & Imberger, 2017) and that it is a significant contributing factor in fatal and serious injury crashes (e.g. Beanland et al., 2013; Overton et al., 2014).

Drivers in Australia engage in a wide range of non-driving activities (Young et al., 2019). These include interactions with infotainment systems provided by vehicle manufacturers. A recent US study found that interacting with the visual display unit (VDU) in a vehicle carries a nearly five-fold increase in crash risk (Dingus et al., 2016).

Aim and Scope

Not all technologies in new vehicles introduced to the market are equal in terms of their potential to distract. The same technologies are often designed and implemented in very different ways by different manufacturers. Consequently, some vehicle cockpits are more demanding of drivers' attention than others and are more likely than others to distract them

(Strayer et al., 2017). This oral presentation will report on the outcomes of an Australian study, commissioned by the Victorian Department of Transport (DoT) (formerly VicRoads), designed to develop a test protocol for rating the distraction potential of new vehicles entering the Australian market, along with a Road Map for its introduction as a consumer or New Car Assessment Program (NCAP) rating.

Materials and Methods

This project, undertaken by the Australian Road Research Board (ARRB), in collaboration with the Victorian DoT, had three components (Regan, Cunningham & Paine, 2018; Paine & Regan, 2018):

1. Research to: (a) determine how the current New Car Assessment Program (NCAP) safety rating processes operate; (b) review human-machine interface (HMI) guidelines and criteria relevant to the assessment of driver distraction; (c) identify and assess the suitability of potential test methods; and (d) identify other human factors literature applicable to the development of a distraction safety rating system.
2. Development of a draft distraction safety rating system.
3. Development of a Road Map that outlines how a distraction safety rating system might be incorporated into NCAP ratings, how it could operate as a standalone process and what other potential pathways for implementation of the system could be followed.

The specific activities involved in progressing these three components, and outcomes of them, will be discussed during the oral presentation.

The project was overseen by two committees: a Scientific Advisory Committee and a Ratings Advisory Committee. These were comprised of local and international distraction and HMI design experts, and vehicle safety rating experts, respectively. The project was undertaken in collaboration with two distraction experts from the University of Utah, who were engaged in similar work at the time (Strayer et al., 2017).

Findings

Based on the literature reviewed, and consultation with members of both Committees, three out of a total of nine identified candidate assessment methods were judged to be most suitable for evaluating the distraction potential of the in-vehicle HMI (the first step in developing a distraction rating system):

1. the Detection Response Task (DRT),
2. the Visual Occlusion Test (VOT), and
3. HMI design guidelines.

The DRT is an internationally recognised and validated measure of cognitive demand (ISO, 17488). The VOT is, similarly, an internationally recognised and validated measure of visual demand (ISO, 16673). These two measures are already used by some vehicle manufacturers to assess the visual and/or cognitive demand of selected infotainment tasks during the design process. The HMI design guidelines, referred to above, were developed by the Australian project team, and were derived from various existing vehicle HMI design guidelines and standards (e.g. NHTSA, 2013). Together, these three methods were judged by the Project Team and Scientific Advisory Committee to be capable of being combined to measure and rate the potential for distraction deriving from driver interactions with in-vehicle infotainment systems (Regan, Cunningham, & Paine, 2018).

Conclusion

A voluntary scheme for encouraging vehicle manufacturers to produce less distracting vehicle HMIs is considered, in the short term, to be the most feasible approach for implementation of a rating system, with a longer-term vision of incorporating the test method into consumer rating systems such as NCAP (Paine & Regan, 2018).

An HMI distraction rating system that is credible to industry and consumers appears feasible but requires further validation and possibly demonstration of its potential to reduce crashes - similar to evidence requirements directing the policies of Australasian/European NCAPs. A proof-of-concept study is currently being undertaken that will employ the distraction safety rating system described in this oral presentation to rate the distraction potential of a small number of new Australian vehicles. If the proof-of-concept study proves successful, a follow-up study, with a larger number of vehicles available for distraction assessment, will need to be undertaken. Ideally this would be with involvement of international research/rating organisations so that it becomes an international project and could be readily adopted by consumer rating organisations such as NCAPs.

The resulting rating protocol could be used by these organisations to rate new vehicles coming to market for their distraction potential. It would also assist manufacturers to design less-distracting in-vehicle HMIs. Our initial economic analysis of the cost of distraction-related crashes and potential trauma savings suggests a very high cost-effectiveness for improved HMI and that this issue should be high on the list of road safety funding priorities.

Acknowledgment:
Two of the authors of this paper, Michael Regan and Mitchell Cunningham, undertook this research whilst previously employed by the Australian Road Research Board (ARRB) and acknowledge the ARRB for its support in enabling them to do the research. The authors gratefully acknowledge the support of Professor David Strayer and Associate Professor Joel Cooper, from the University of Utah (USA), and Dr David Yang from the AAA Foundation for Traffic Safety in the USA, for their expert knowledge, advice and assistance with the project. The authors also gratefully acknowledge the support of the Australasian New Car Assessment Program (ANCAP), especially in chairing the Ratings Advisory Committee, and the support of the local and international members of the Scientific and Ratings Advisory Committees for their inputs to the project. The Victorian Department of Transport commissioned the Australian Road Research Board (ARRB) to undertake the project, which was was funded by the Victorian Government’s Transport Accident Commission (TAC) under its *Towards Zero 2016//2020 Road Safety Strategy and Action Plan*.

References

Beanland, V., Fitzharris, M., Young, K. & Lenne, M. (2013). Driver inattention and driver distraction in serious casualty crashes: Data from the Australian Crash In-Depth

Study. *Accident Analysis and Prevention,* Vol 54, pp 99-107.

Cunningham, M., Regan, M., & Imberger, K. (2017). Understanding driver distraction associated with specific behavioural interactions with in-vehicle and portable technologies. *Journal of the Australasian College of Road Safety*, *23*, 27 – 40.

Dingus, T., Guo, F., Lee, S., Antin, J., Perez, M., Buchanan-King, M., & Hankey, J. (2016). Driver crash risk factors and prevalence evaluation using naturalistic driving data. *Proceedings of the National Academy of Sciences*, *113*(10), 2636-41.

International Organisation for Standardisation (ISO) (2016). ISO 17488:2016 - *Road vehicles -- Transport information and control systems -- Detection-response task (DRT) for assessing attentional effects of cognitive load in driving. International Organization for Standardization*. Retrieved 13 September, 2019, from https://www.iso.org/standard/59887.html

International Organisation for Standardisation (ISO) (2017). *ISO 16673:2017 - Road vehicles — Ergonomic aspects of transport information and control systems — Occlusion method to assess visual demand due to the use of in-vehicle systems. International Organization for Standardization*. Retrieved 31 January, 2020, from https://www.iso.org/standard/71508.html

Klauer, S. G., Guo, F., Simons-Morton, B. G., Ouimet, M. C., Lee, S. E. & Dingus, T. A. (2014). Distracted driving and risk of road crashes among novice and experienced drivers. *New England Journal of Medicine, 370,* 54–59.

National Highway Traffic Safety Administration (NHTSA), (2013). *Visual-Manual NHTSA Driver Distraction Guidelines for In-Vehicle Electronic Devices*. National Highway Traffic Safety Administration, Department of Transportation: Washington, DC, USA. Retrieved June 8, 2019, from https://www.federalregister.gov/documents/2013/04/26/2013-09883/visual-manual-nhtsa-driver-distraction-guidelines-for-in-vehicle-electronic-devices

Olson, R. L., Hanowski, R. J., Hickman, J. S., & Bocanegra, J. (2009). *Driver distraction in commercial vehicle operations* (Report No. FMCSA-RRR-09-042). Washington, D.C.: U.S. Department of Transportation.

Overton, T.L., Rives, T.E., Hecht, C., Shafi, S., Gandhi, R.R. (2014). Distracted driving: prevalence, problems, and prevention. *International journal of injury control and safety* 32, 1-6.

Paine, M. & Regan, M.A. (2018). *Road Map for an HMI Distraction Safety Rating (Component 2; Deliverable 5)*. Sydney: Australian Road Research Board (report available from Department of Transport, Victoria).

Regan, MA., Cunningham, ML., & Paine, M. (2018). *Towards Zero Distraction Project: Final Report - Overview of Project Findings and Next Steps (Deliverable 6)*. Sydney: Australian Road Research Board (report available from Department of Transport, Victoria).

Regan, M. A., Hallett, C & Gordon, C.P., (2011). Driver distraction and driver inattention: definition, relationship and taxonomy, *Accident Analysis & Prevention*, *43*(5), 1771-81.

Strayer, D, Cooper, J, Goethe, R, McCarty, M, Getty, D & Biondi, F. 2017, *Visual and Cognitive Demands of Using In-Vehicle Infotainment Systems*, AAA Foundation for Traffic Safety, Washington DC, USA.

Young, K., Osborne, R., Koppel, S., Charlton, J., Grzebieta, R., Williamson, A., Haworth, N., Woolley, J. & Senserrick, T. (2019). What are Australian drivers doing behind the wheel? An overview of secondary task data from the Australian Naturalistic Driving Study. *Journal of the Australasian College of Road Safety*, *30*(1), 27-33.

Exploring the prevalence of in-vehicle distraction in moving traffic: An observational study using camera technology

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Keywords: In-vehicle distraction, observational study, phone use, prevalence, technology

ABSTRACT

Introduction

Given the crash risk associated with driver distraction [e.g. 1]and the potential increase in in-vehicle technology-related distractions, the development of a method to monitor the prevalence and types of driver distraction over time is important for identifying trends (and potential countermeasures) for such behaviors. Observation of drivers while moving in traffic can provide objective information about the prevalence of specific distractions within the vehicle. Recording video of drivers in traffic is an innovative unobtrusive means of obtaining data on driving-related distractions and avoids issues related to self-reporting errors and the effect of changing behaviors while being monitored [2]. In addition, it allows observations of a large number of vehicles within a relatively short time frame. This exploratory study sought to determine whether camera technology is suitable for observing a variety of distracted driving behaviors among drivers in moving traffic on public roads and to provide an indication of the prevalence of different distracting behaviors by location and gender.

Method

Four locations around Adelaide, South Australia, were selected for video camera observations of distracted driving behavior in low speed and high speed traffic environments. Elevated locations were used so that drivers could be observed using a system of three strategically placed cameras (i) on their approach, from afar (ii) zoomed in to the driver's compartment directly from above and (iii) zoomed in from an angled perspective to capture the driver.

Around 90 minutes of video footage was recorded at each location. For each period of recorded video footage, a 30-minute observation period was selected and used in the analysis to identify any distracted behaviors.

Results

In the two-hour sample period across the four sites, 920 drivers were observed, of whom

8.9% (n=82) were engaged in some form of distracted behavior. Table 1 shows the number and type of distractions observed. Of those who were distracted, 28.1% (n=23) were observed engaging in mobile phone use while driving. The most frequently observed distracted behavior, aside from mobile phone use, was searching for, or holding an object (20.7%), eating/drinking (17.1%), wearing headphones (9.8%) and smoking (7.3%).

Table 1. Driver distractions coded at each location

Distraction	1	2	3	4	Total	Per cent
1. Mobile phone - Talking (phone to ear)	-	-	-	1	1	0.1%
2. Mobile phone - Active touching (texting etc)	-	-	1	1	2	0.2%
3. Mobile phone - Hands-free (touching in cradle)	-	1	4	-	5	0.5%
4. Mobile phone - Holding	1	-	6	-	7	0.8%
5. Mobile phone – On lap (passive)	1	3	2	2	8	0.9%
6. Touching navigation system /other tech	-	-	-	-	-	0.0%
7. Adjusting controls	1	1	-	1	3	0.3%
8. Wearing headphones	1	-	3	4	8	0.9%
9. Eating/drinking	1	3	6	4	14	1.5%
10. Smoking	-	2	1	3	6	0.7%
11. Searching for (or holding) object	3	6	5	3	17	1.8%
12. Reading	-	-	-	-	-	0.0%
13. Grooming (& looking away)	-	-	-	1	1	0.1%
14. Attending to/touching passengers or animals	1	2	-	-	3	0.3%
15. Likely/possible distraction (nature unknown)	1	-	3	1	5	0.5%
16. Other	1	1	-	-	2	0.2%
No Distraction	123	320	294	101	838	91.1%
Total	134	339	325	122	920	100.0%

Of the drivers who were observed as being distracted 74.4% were male, 22.0% were female and in three cases the gender could not be determined. Examples of driver distractions extracted from the video footage are shown in Figure 1.

Figure 1. Examples of driver distractions. The top three images show ‘Mobile phone –

holding' for the same driver as seen in the three different camera views. The bottom three images show various examples of 'Eating/drinking' and 'Smoking'.

The proportion of drivers engaging in distracted behavior decreased as the road speed limit increased. This result was statistically significant between 50 km/h and 60 km/h speed zones ($p<0.01$) and 50 km/h and 100 km/h speed zones ($p<0.001$), however the difference between 60 km/h and 100 km/h was not significant ($p=0.06$).

Generally, the prevalence of distractions observed in this study using on road observations was of a similar magnitude to those reported in crashes. In Australia, a recent analysis of fatal and injury crashes found 7.5% of crashes were due to in-vehicle distractions with 2.5% attributed to phone use [3]. Similarly, an analysis of fatal crashes in Norway reported 2-4% of crashes were due to phone use [4]. These findings are also relatively consistent with recent data from the Australian Naturalistic Driving Study (ANDS) examining secondary task engagement. The study found mobile phone use was observed in 7.4% of the secondary tasks [5].

Conclusions

This explorative study has demonstrated that there is technology suitable for observing distracted driving behavior among drivers in moving traffic on public roads which could potentially be deployed for a larger, more representative study. The method used provides a reasonably objective snapshot of distracted behavior, although some judgement is required when viewing the footage. The observation and coding processes are quite labour intensive but it is anticipated that this will decrease as the technology progresses through automated detection, machine learning and artificial intelligence. A method of validating the findings in a larger study would involve randomly selecting at least 20 locations, weighted by geographical distribution, including various road types (high volume, low volume, different speed zones, urban and rural) and sampling 24 hours on a weekday and weekend. A significant number of vehicles (e.g. 2,500 or 10,000 vehicles) would be randomly selected from the pool of vehicles recorded (weighted by day of week and by traffic flow numbers at each location). This study provided some evidence to suggest that drivers were less likely to engage in distracted behaviors when travelling at higher speeds.

Acknowledgments

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References:

[1] Klauer, S., Guo, F., Simons-Morton B., Ouimet M., et al.: 'Distracted driving and risk of road crashes among novice and experienced drivers'. N. Eng. J. Med., 2014, 370 (1), pp. 54-59.

[2] Huisingh C, Griffin R, McGwin G Jr:. 'The prevalence of distraction among passenger vehicle drivers: a roadside observational approach', Traffic Inj. Prev., 2015, 16 (2), pp. 140–146.

[3] Wundersitz, L.: ‘Driver distraction and inattention in fatal and injury crashes: Findings from in-depth road crash data’. Traffic Inj. Prev., 2019, 20 (7), pp696-701.
[4] Sundfør, H.B., Sagberg, F., Høye, A.: ‘Inattention and distraction in fatal road crashes – Results from in-depth crash investigations in Norway’. Acc. Anal. Prev., 2019, 125, pp. 152-157.
[5] Young, K.L., Osborne, R., Koppel, S., Charlton, J.L., et al.: ‘What are Australian drivers doing behind the wheel? An overview of secondary task data from the Australian naturalistic driving study’. J Aust Col Road Safety, 2019, 30, pp. 27-33.

Method to assess driver behaviour following distractions external to the vehicle – 2020

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Keywords: Digital Billboard, Driver Distraction, EEG, Eye tracking, Driving Simulation

ABSTRACT

This study used a synchronised eye tracking and electroencephalogram (EEG) system to examine the effect of external (static and dynamic) distraction on driver's visual and cognitive responses to digital billboards. The EEG was used to eliminate any concerns about differences in workload or fatigue within participants. The eye tracking served as a function of attention for participants as they passed billboards. It was predicted that if there was evidence of increased attention over the billboard, it would be more prevalent over dynamic billboards. Driving performance was also examined in relation to the events the participants were witnessing.

A customised driving simulator was made using Unity. The driving simulator consists of a straight road. Along the left side of the road, there are 50 speed limit signs, randomly placed. The speed limits vary between 40km/h, 60km/h and 80 km/h. Along the right side of the road, there are 50 digital billboards placed opposite to the speed sign. The digital billboards were randomly sorted. Half of the billboards were dynamic (changing image) and the other half were static. The billboards content were a combination of advertising and road messages. Each dynamic billboard changed the content as the car approached the speed sign at a predefined distance. The experiment utilised a Logitech G27 racing wheel and pedal for the participants to control the car in the simulator. The participants were told to obey the rules of road and observe speed limits. Steering on the simulator was disabled, but participants had control of the pedals.

The EEG acquisition system used was the g.Tec g.USBamp. The EEG recorded at 512 Hz with 16 active electrodes. The eye movement data was recorded with Tobii X-120 eye tracking system. The sampling rate of this system was 120Hz. Fixations and saccades were identified with velocity threshold of 80°/second [1]. Calibration accuracy was controlled within 1.5 degrees. Participants were seated at 100 cm from triple head monitor (Matrox TripleHead2Go). The collection of driving simulator car position data, EEG data, and eye tracking data were synchronised using the lab streaming layers (LSL) [2].

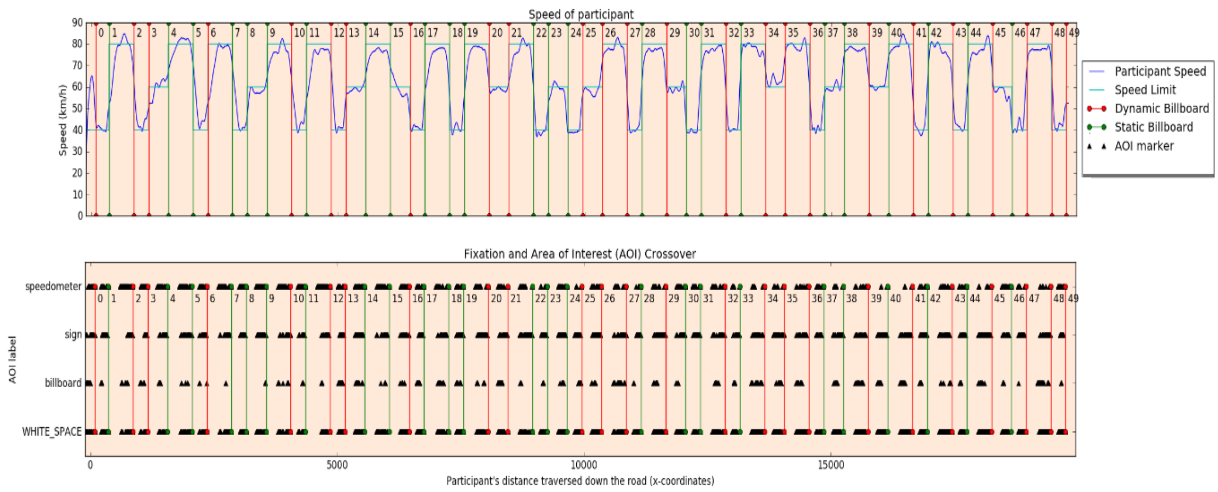
EEG data was pre-processed using EEGLAB (14.1.1) under Matlab (R2016) [3]. The data first applied finite impulse response (FIR) filter at 0.1 to 30 Hz to remove DC and high

frequency noise. Artefact correction using independent component analysis (ICA) to detect noisy components were then removed from the data. EEG band powers were determined using the Multitaper power spectral density estimate. Relative power was computed as a ratio to power prior to distractor events to during. Utilising the positions of the electrodes they were split and averaged into frontal (AF3, AF4, F7, F8), central (Cz, T7, T8), parietal (P1, P2, Pz, P7, P8, CP5, CP6), and occipital (O1, O2) sites.

The eye-gaze data was initially processed to identify times when tracking was lost. Interpolation was used correct short periods of tracking loss. The data was converted from units of pixel location to degrees to allow eye velocity measurements. A five-point Gaussian running average (FIR) filter was used to reduce noise.

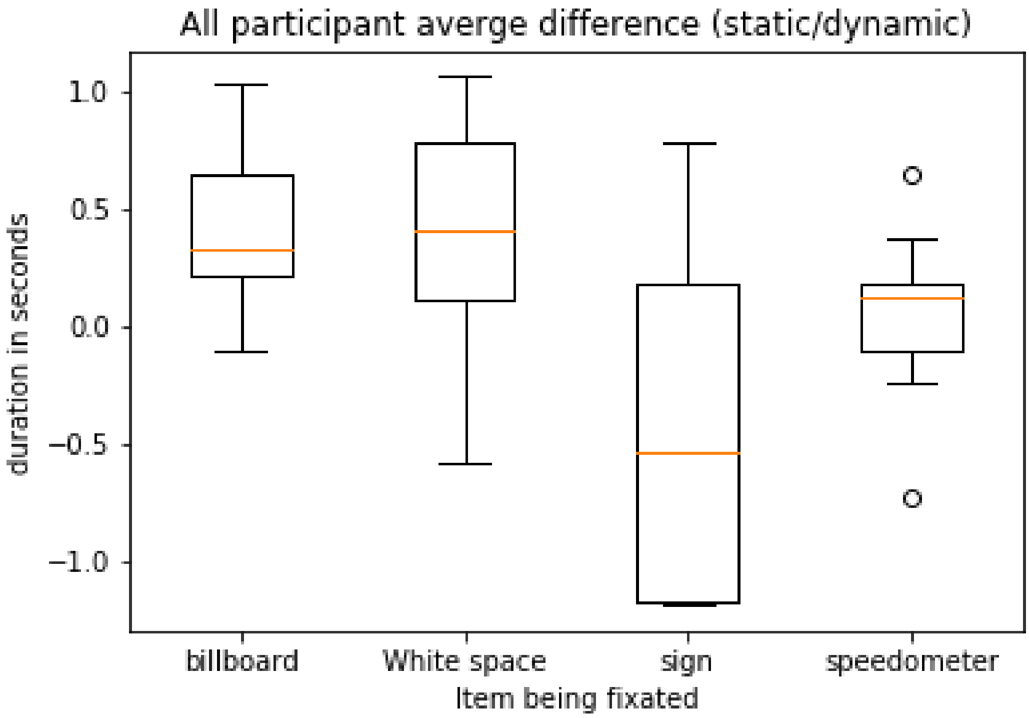
An example of the data for a single participant can be seen in Figure 1. The two graphs show driver speed, and eye-tracking information plotted against distance along the driving route for one participant. Red lines indicate the position of dynamic billboards, green lines correspond to the position of static billboards. The driver speed graph shows speed limit in green horizontal bars and driver road speed using blue lines. The eye-tracking plot identifies target fixations to areas of interest as a function of road position.

Figure 1. Single participant data while navigating the driving simulation



The data collected was analysed to show the drivers overall response over the duration of the experiment. For each of the 9 participants their eye gaze data was represented as fixations over areas of interest (white space, speedometer, billboard, sign). To test for differences between static and dynamic billboards the averages for dwell time over the areas were calculated for each event and the difference of these averages were plotted, see Figure 2. A paired t-test on each of the average dwell time differences showed that the billboard dwell time differences had a significant effect size, with a p-value <0.05 and t-value of 3.677. This contradicts the null hypothesis that the average difference of dwell time over the dynamic billboard has either less time or zero difference to the static billboard dwell time. The driver controls were represented as the root mean squared error (RMS) between the speed limit and the actual speed the participant travelled at, and the standard deviation of the participants speed (σ_{Speed}) at each of these intervals. A paired t-test was carried out for each driver performance variable with respect to the static and dynamic averages. There was no statistically significant difference for the RMS but there was for the standard deviation size of their speed ($\alpha<0.05$). The mean of the differences for the standard deviation of the speed was 1.48km/hr. Alpha, beta, theta, and delta power spectral densities were averaged second to second for static versus dynamic events at the sites listed above. There were no statistically significant effects witnessed ($\alpha<0.05$) with ANOVA tests while considering the differences in the averages of the group.

Figure 2. Average difference of fixation dwell times in static and dynamic billboard events.



Using averaged data across the 9 participants (50 billboards) it suggests that there is an increased fixation time for dynamic billboards over static billboards. The dynamic billboards each required an average additional 0.41 seconds fixation time per short sequence (between 15-20 seconds at each billboard). The speedometer fixations over these periods remained relatively constant. The other two groups appear to have high variability in fixation dwell times. There is a slight increase in the variability in driving speed following a dynamic billboard when compared to a static billboard. It appears that driver performance deteriorates marginally from a single dynamic billboard event. Further testing with more intricate distracting events on billboards (more transitions or video/animation based) may elicit a stronger response in terms of driver performance.

References:

[1] Olsen, A., 2012. The Tobii I-VT fixation filter. *Tobii Technology*, pp.1-21.

[2] Kothe, C., Medine, D. and Grivich, M., 2018. Lab Streaming Layer (2014). *URL: https://github.com/sccn/labstreaminglayer (visited on 02/01/2019)*.

[3] Delorme, A. and Makeig, S., 2004. EEGLAB: an open source toolbox for analysis of single-trial EEG dynamics including independent component analysis. *Journal of neuroscience methods*, *134*(1), pp.9-21.

Distraction Assessment Methods: To What Extent Does a Detection Response Task (DRT) Impact Apparent Workload?

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Keywords: Attention, cognitive workload, driver distraction, heart rate, n-back

ABSTRACT

Visual and manual forms of driver distraction are, at least conceptually, directly observable events (e.g., eye glance directed away from the roadway, removal of a hand from the steering wheel to rotate a control knob). Cognitive workload / distraction, however, must largely be inferred by indirect means. The Detection Response Task (DRT) method has been investigated and standardized by the International Organization for Standardization (ISO) specifically to support a means for assessing the attentional demands of cognitive load arising from engagement with driving information and control systems (ISO 17488) [1]; it can similarly be applied to other sources of cognitive engagement (e.g., a cellphone conversation, mind-wondering). While the DRT has been validated as a sensitive technique for detecting scaled levels of cognitive demand [2], it seems reasonable to ask whether, and to what extent, the DRT task impacts the underlying workload and behavior the driver?

Two studies were conducted in a full cab, medium fidelity driving simulator. Self-reported workload, driving performance (lane discipline, speed control), and heart rate data were collected while ‘just driving” and driving while engaging in multiple levels of an auditory presentation – vocal response working memory task (n-back; see [2,3]) designed to systematically manipulate cognitive workload. In addition to standard 0-, 1, and 2-back levels, a “blank-back’ condition in which participants simply listened to a series of single digit numbers, but without a requirement to respond, was included. Participants in the analysis samples were balanced by gender and equally distributed across the 4 NHTSA-recommended [4] age groups of 18-24, 25-39, 40-54, and 55+. The sample in Study 1 consisted of 48 participants who engaged in the aforementioned conditions with and without concurrently being presented with a visual DRT consisting of a head-mounted LED stimulus system and micro-finger switch response configuration that was implemented in conformance with ISO standard [1]. A second study with 24 participants further considered a tactile DRT following the ISO standard.

The combined data from the head-mounted visual DRT and tactile DRT studies provide a fairly consistent picture. First, as expected, the 0-, 1-, and 2-back levels of the n-back cognitive demand task produced statistically significant and relatively equally stepped increases in workload as measured by self-report (Figure 1) and heart rate indices (Figure 2). This result was seen in both studies, and was present when

participants were engaged in a dual task paradigm (driving the simulator and doing an n-back task) and in a triple task paradigm (driving the simulator, an n-back task, and a DRT or TDRT task).

Figure 1. Self-reported workload ratings (0 low to 10 high) across all conditions without and with a DRT (head-mounted visual DRT on the left and tactile DRT to the right in each pair). Error bars represent ±1 within-subject SEM.

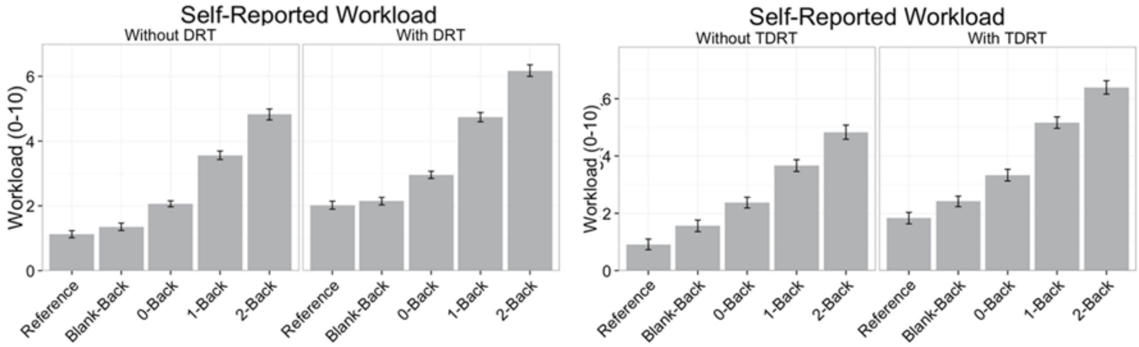
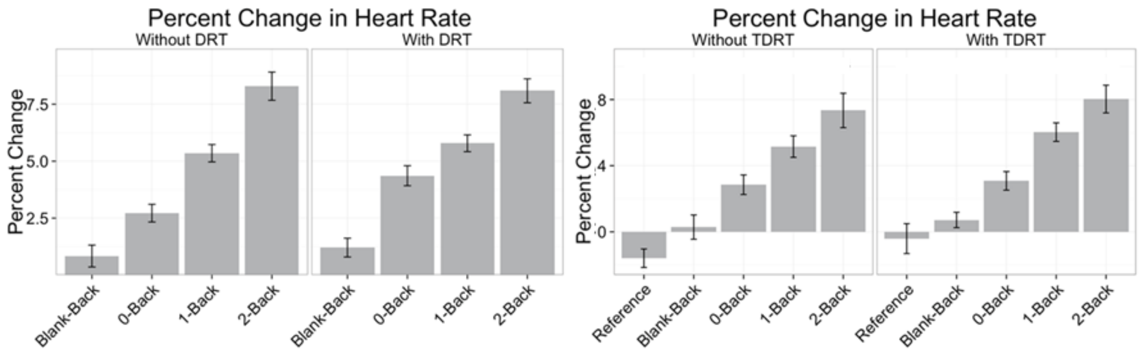


Figure 2. Percent change in heart rate from a baseline driving period compared to all task periods without and with a DRT (head-mounted visual DRT on the left and tactile DRT to the right in each pair). Error bars represent ±1 within-subject SEM.



In terms of sensitivity / scaling, both self-report and heart rate scaled “just driving” and driving with each of the levels of the n-back in the expected order based on objectively defined working memory demand. Similarly, the head-mounted DRT and TDRT reaction time measures also correctly ordered the task conditions. The DRT and TDRT miss-rate measures generally increased with task demand, but did not successfully discriminate all levels from each other. Thus, while the miss-rate metric is heuristically appealing as a distraction measure, the reaction time metric appears to be more appropriate for scaling purposes. This finding is in-line with the recommendations of the standard that specifies reaction time as the primary metric.

Core questions of this work concerned the extent to which the DRT methodology adds to the overall demand placed upon the driver or otherwise influences the pattern of results obtained in evaluating apparent cognitive demand associated with a task. In terms of self-reported workload, participants reported significantly higher levels of workload when engaged with the head-mounted DRT and TDRT than when they were not engaged in the added tasks. However, this did not impact the relative scaling of task levels and it did not translate into significantly higher levels of physiological arousal as measured by heart rate. Consequently, while perceived workload was higher when participants engaged with the head-mounted DRT or TDRT, the use of the DRT methods to establish the relative scaling of cognitive demand associated with the secondary tasks under study appears quite reasonable.

It is more difficult to make as definitive a statement about whether or not engaging in DRT tasks impacted other aspects of driver behavior. A priori, adding a DRT task increased the objective demand on the drivers, and this is reflected in their higher self-reported workload under the DRT conditions. However, physiological arousal levels were comparable with and without the DRT tasks. This suggests that drivers engaged in some form of compensatory behavior to maintain similar arousal level under both conditions. To the extent that this was the case, the overall impact on behavior patterns was subtle. No clear impact on driving speed was observed. N-back performance at the 2-back level was lower and SD of velocity was nominally higher when doing the DRT in Study 2, but this pattern was not as evident in Study 1. These latter findings largely align with [5] that found that a visual DRT increased secondary task time (a compensatory response) but had no significant effect on driving performance.

While these findings are seen as largely positive for the DRT methodology, some cautions in generalizability are suggested. The two studies reported were carried out under a relatively low demand driving scenario consisting of a two-lane rural highway, with low traffic density, a posted speed limit of 50 mph, and only occasional, gradual curves requiring minimal active steering. This scenario was intended to be in relative, although not exact, conformity with the assessment scenario described by NHTSA in the original draft visual-manual distraction guidelines for the assessment of in-vehicle electronic devices. Consequently, while the triple task of driving the simulator, engaging in a 2-back task, and responding to a DRT stimulus was reasonably demanding, the data collected suggest that most, if not all, participants did not exceed the limits of their spare cognitive capacity to deal with these combined demands. The extent to which different results might be obtained as such spare capacity is further taxed or exceeded, is an open question.

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References:

[1] ISO 17488:2016: 'Detection-response task (DRT) for assessing attentional effects of cognitive load in driving.', ISO, Geneva, Switzerland, 2016.

[2] ISO/TS 14198:2019(E): 'Calibration tasks for methods which assess driver demand due to the use of in-vehicle systems.', ISO, Geneva, Switzerland, 2019.

[3] Mehler, B., Reimer, B. & Coughlin, J.F.: 'Sensitivity of physiological measures for detecting systematic variations in cognitive demand from a working memory task: an on-road study across three age groups', Hum. Fact., 2012, 54, (3), pp. 396-412.

[4] National Highway Traffic Safety Administration (NHTSA): 'Visual-Manual NHTSA Driver Distraction Guidelines for In-Vehicle Electronic Devices (Docket No. NHTSA-2010-0053)', U.S. Dept. of Transportation, NHTSA, Washington, DC, 2013.

[5] Broström, R., Kumar Chilakapati, R., & Rydström, A.: "Intrusiveness of a visual detection task on secondary and driving task performance", Proceedings 1st Inter. Conf. on Driver Distraction and Inattention, 2009, Arcueil, France.

Quantifying attentional demand of a lane-keeping task as the minimum required information in predictive processing

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Keywords: inattention; distraction; attentional demand; relative entropy; surprise

ABSTRACT

There is no clear consensus about the theoretical definition and operational criteria of inattention or distraction in traffic, which may lead to conflicting conclusions in research [1]. The scientific community should have a consensus on the definition and operationalization of driver inattention in order to provide strong guidance, for instance, in the planned distraction assessment incorporated into EuroNCAP ratings, the new distraction legislation, and development of driver attention monitoring systems.

Some researchers may consider any competing glance away from the forward driving scene as distraction (e.g., [2]), whereas others have stressed that often drivers have spare visual capacity in driving (e.g., [3]). There is also no agreement on if a certain off-forward glance duration (e.g., 2 seconds [4]) can be considered as a general time threshold for visually distracted driving. The most popular definitions (e.g., [1][5]) suggest that glancing away from the forward driving scene is visual distraction only if it prevents the driver to perform "activities critical for safe driving". However, these taxonomies have not offered clear guidance on how this criticality should be defined or measured for different driving scenarios. Kircher and Ahlström [6] as well as Regan et al. [1] discuss hindsight bias in defining and measuring inattention. The bias refers to defining drivers as being inattentive based on the observed outcomes of a situation (e.g., a crash or a lane excursion). This is an inappropriate way to operationalize inattention, as we should know if the driver is attentive towards the driving task regardless of the outcome.

The proper way to operationalize driver inattention would require a baseline of attentive driving, that is, to define to which driving-relevant targets attention and how much, should a driver allocate for successful task performance in a given scenario (i.e., the attentional demands of driving). For scientific, engineering and regulatory purposes, it would be highly useful to have well-founded and quantifiable metrics of attentional demand and inattention applicable for various driving scenarios and, for instance, different simulations of the driving task. This contribution continues the construction of a computational framework for quantifying attentional demands of driving presented at DDI2018 [7] based on the valuable feedback from the audience.

Quantification of attentional demand of driving-relevant event states

The presented approach for modelling the dynamic information requirements of a human driver is based on the predictive processing frameworks of cognition [8][9] and relative entropy as a measure of potential information gain (i.e., Bayesian surprise [10]). The predictive processing framework of cognition [8] stresses the importance of prediction uncertainty and its resolution in human attention allocation and behaviour. Uncertainty of a belief distribution (i.e., prediction) can be computationally modelled by its entropy [10]. However, entropy of a driver's belief distribution of an upcoming driving-relevant state (e.g., distance to lead car) cannot be used directly as a measure of the *normative* attentional demand for the driver, as drivers may have inaccurate beliefs and false confidence on these [11]. This is why the attentional demand is better to be quantified with relative entropy [10]. Here, relative entropy refers to the potential information gain (i.e., potential surprise, S) for a driver's belief distribution Q of state x relative to a task-critical threshold T(x), if the driver samples the information at time t (i.e., Kullback-Leibler divergence: $S(x>T(x),t) = D_{KL}[P(x>T(x),t)||Q(x>T(x),t)]$). Zero S indicates no attentional demand towards x. This definition of attentional demand of a driving-relevant event state is dependent on task-critical threshold(s) and volatility of the state behaviour, which is affected by driver's actions based on subjective belief distribution of the state. It is well in line with the theoretical frameworks of the brain as an adaptive Bayesian prediction machine (e.g., [8]), which are currently popular in cognitive neuroscience. In this framework, inattention is a form of *inappropriate uncertainty* [9] in relation to the volatility of a task-relevant state and task goal(s).

Example: Quantification of attentional demand and inattention in lane keeping

Here, the application of this framework for the operationalization and measurement of attentional demand and inattention is illustrated for a simple lane-keeping task. The oral presentation will also review empirical evidence on the feasibility of the framework in this task, collected in a driving simulator. Figure 1 illustrates what the definition means for a simplified lane-keeping task under occlusion [12][13] and with a constant speed.

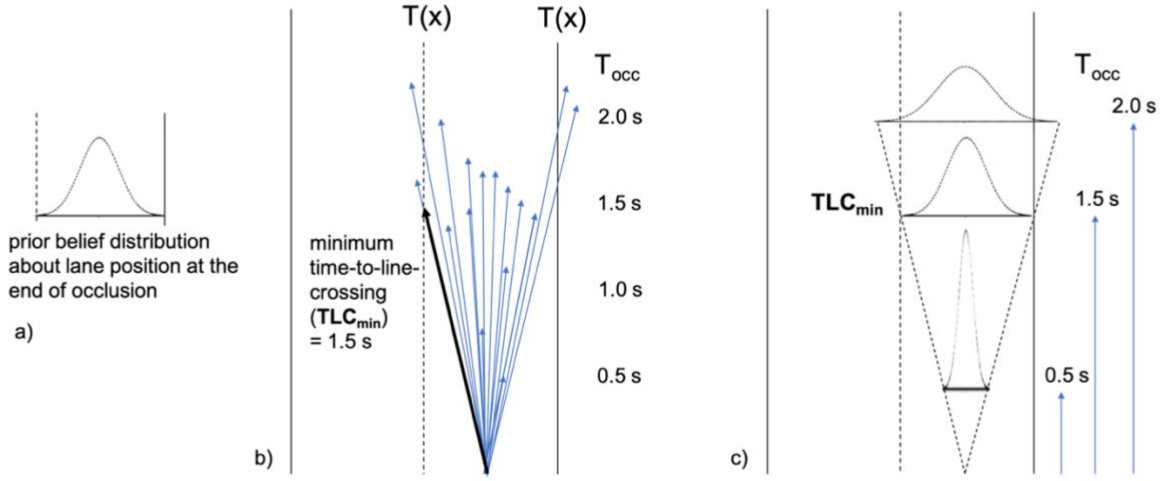

Figure 1. a) Driver's assumed prior belief distribution about lane position (x) at the end of each occlusion $[Q(x,T_{occ})]$. b) Measurements of the driver's true paths during repeated occlusions and the minimum time-to-line-crossing (TLC_{min}). c) Probabilities of lane position at three time points based on the measurements $[P(x,T_{occ})]$. Potential surprise relative to a task-critical threshold T(x) for the lane position belief starts to grow at 1.5 seconds.

In this task, the driver is instructed to keep the own lane while driving occluded, and to end the occlusion at the moment when feeling it is possible the car is leaving the lane. At each sampling, we can therefore assume driver's prior belief distribution about the lane position to resemble Fig. 1 a) (as an example), with minimum and maximum subjectively possible values at the lane boundaries (i.e., "extreme hypotheses"). Fig 1. b) illustrates measurements of the driver's true paths during repeated occlusions and the minimum time-to-line-crossing (TLC_{min} [14]) while occluded. Fig. 1 c) indicates probabilities of lane position at three points in time based on the measurements. In this example, potential surprise (S) relative to the lane boundaries T(x) for the lane position belief starts to grow rapidly after TLC_{min} (1.5 s), corresponding to a minimum sampling requirement of once per 1.5 s, to (probably) succeed in the task (NB. Reaction time and time required for corrective steering are not included in this example.). Sampling the lane position less than once per 1.5 s in similar future situations would then indicate inattention (i.e., inappropriate uncertainty), regardless of the outcome of the situation. If we knew all the relevant variables that affect this minimum sampling threshold (e.g., lane width, curvature, speed, TLC, steering amplitude), and how much, we would be able to estimate the normative situational minimum information sampling frequency in this particular task for the driver at any situation. Note that in this exactly same task, the minimum required information sampling frequency can vary between drivers and for a driver, depending on the situational and driver-specific variables (e.g., steering input). The illustration is highly simplified but the same principle applies to more winding paths and driving in curves.

Discussion

The introduced framework seems to work well for the studied part-task of driving, that is, lane keeping with fixed speed. A simplified driving task may suffice as a well-founded baseline for, for instance, in-car tasks' visual distraction potential benchmarking in controlled simulator environments. The framework should work well also for other continuous tracking-based part-tasks, such as longitudinal control, for which the occlusion method [12] can be applied to. Applicability of the approach to more realistic driving with multiple concurrent and interacting demands should be evaluated. Furthermore, its generalization to discrete driving-relevant events based on more static demands of the road environment or infrastructure (see e.g., [6]) should be further studied. At least, as opposed to a more frequentist approach, the framework suggests that the attentional demand of looking at both directions while approaching a T-crossing is independent of the traffic density in the crossing and never zero, as there is always a possibility of an approaching vehicle.

The proposed operationalization and quantification of attentional demand and inattention is probabilistic, and thus, free of hindsight bias [1][6]. The approach may also be accepted even if one is not a supporter of the predictive processing approach to human cognition [8]. The sole cognitive assumption that must be accepted is that drivers can have mental representations of driving-relevant event states and that they are able to drive based on these, at least for limited periods of time. There is empirical evidence available that supports this assumption (e.g., [15]). In future studies, it will be interesting to study the generalizability of this approach to quantify attentional demands of tasks beyond manual driving and to develop driver (in)attention monitoring algorithms (cf. [16]) based on it.

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References:

[1] Regan, M.A., Hallet, C., Gordon, C.P.: 'Driver distraction and driver inattention: Definition, relationship and taxonomy', Accident Analysis & Prevention, 2011, 43, 1771–1781

[2] Foley, J.P. Young, R., Angell, L., Domeyer, J.E.: 'Towards operationalizing driver distraction', Proceedings of the 7th International Driving Symposium on Human Factors in Driver Assessment, Training, and Vehicle Design, 2013, 57–63

[3] Kircher, K., Kujala, T., & Ahlström, C.: 'On the difference between necessary and unnecessary glances away from the forward roadway: An occlusion study on the motorway', Human Factors, 2020, 62, 1117–1131

[4] National Highway Traffic Safety Administration: 'Visual-Manual NHTSA Driver Distraction Guidelines for In-Vehicle Electronic Devices' (Washington DC, NHTSA 2013)

[5] Engström, J., Monk, C.A., Hanowski, R.J., Horrey, W.J., Lee, J.D., McGehee, D.V., Regan, M., Stevens, A., Traube, E., Tuukkanen, M., Victor, T., Yang, D.: 'A Conceptual Framework and Taxonomy for Understanding and Categorizing Driver Inattention' (US-EU ITS Cooperation, Driver Distraction and HMI Working Group 2013)

[6] Kircher, K., Ahlström, C.: 'Minimum required attention: A human-centered approach to driver inattention', 2017, Human Factors, 59, 471–484

[7] Kujala, T.: 'Attentional demand of driving as uncertainty in predictive processing', Book of Abstracts for the 6th International Conference on Driver Distraction and Inattention, 2018, 19–23

[8] Clark, A.: 'Whatever next? Predictive brains, situated agents, and the future of cognitive science', Behavioral and Brain Sciences, 2013, 36, (3), 181–204

[9] Kujala, T., Lappi, O.: 'Inattention and uncertainty in the predictive brain', Frontiers in Neuroergonomics, 2021, 2

[10] Baldi, P., Itti, L.: 'Of bits and wows: A Bayesian theory of surprise with applications to attention', Neural Networks, 2010, 23, 649–666

[11] Engström, J., Bärgman, J., Nilsson, D., Seppelt, B, Markkula, G., Piccinini, G. B., Victor, T.: 'Great expectations: A predictive processing account of automobile driving', Theoretical Issues in Ergonomics Science, 2017, 1–39

[12] Senders, J.W., Kristofferson, A.B., Levison, W.H., Dietrich, C.W., Ward, J.L.: 'The attentional demand of automobile driving', Highway Research Record, 1967, 195, 15–33

[13] Kujala, T., Mäkelä, J., Kotilainen, I., Tokkonen, T.: 'The attentional demand of automobile driving revisited: Occlusion distance as a function of task-relevant event density in realistic driving scenarios', Human Factors, 2016, 58, 163–180

[14] Godthelp, H., Milgram, P., Blaauw, G. J.: 'The development of a time-related measure to describe driving strategy', Human Factors, 1984, 26, (3) 257–268

[15] Kircher, K., Ahlstrom, C., Nylin, M., Mengist, A.: 'Tactical steering behaviour under irrevocable visual occlusion', Transportation Research Part F: Traffic Psychology and Behaviour, 2018, 55, 67–77

[16] Ahlström, C., Georgoulas, G., Kircher, K.: 'Towards a context-dependent multi-buffer driver distraction detection algorithm', IEEE Transactions on Intelligent Transportation Systems, 2021

Evaluation of Driver Visual Distraction in Automated Driving Systems in Driving Simulator, Test Course, and Public Roads Experiments

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Keywords: Automated Driving, Driver Monitoring, Visual Distraction, Eye Movements.

ABSTRACT

Driver monitoring systems are one of the important components to develop automated driving systems. The driver using level 2 and 3 automated systems in the SAE definition [1] should take over the control of the vehicle when the operational domains of the automated systems exceed their functional limitations. Successful controls after the transition might be influenced by driver conditions while the automated systems are active. It is important to identify evaluation indices that detect driver conditions before RtI (Request to Intervene) in order to develop the driver monitoring system for assessing the driver's ability for the safe transition.

Several indices, including eye-related metrics and physiological metrics, have been investigated in human factors research of the automated and manual driving (e.g., [2]). When a driver uses the automated driving systems (especially, the level 3 systems), he/she might be engaged in non-driving related activities, such as reading texts, watching a movie, gaming, searching visual information, and listening to the music. These driver conditions include eye-off-road (visually loaded), mind-off-road (cognitively loaded), and drowsy (low arousal level) conditions.

In this study, we focused on the eye-off-road condition and investigated evaluation indices that can be adapted to non-wearable detection under real road traffic environments, contributing to practical implementation of the driver monitoring systems (see the references [3] for the other driver conditions). The research flow was as follows:

1. Driving simulator experiment

   The aim of this experiment was to select the metrics for assessing the eye-off-road condition within a variety of measurement indices including the index that we could measure only in experimental environments (e.g. brain activities).
2. Test course experiment

   The aim of AIST proving ground experiment was to confirm whether the evaluation indices selected in the simulator study suggested similar tendencies between in the virtual and real environments.
3. Public roads experiment

The aim of this field operational test was to confirm that the assessment methods obtained from the simulator and test course experiments were valid for longer travel duration in real road traffic environments.

The driving simulator consisted a real vehicle cabin, a 6 degrees-of-freedom electric motion system, and a 300-degree field of view screen. 32 drivers (12 females and 20 males, average age: 36.5 years old, average driving experience: 16.2 years) participated in the driving simulator experiment. The automated driving system controlled the vehicle at 80km/h in the left lane and followed a lead vehicle at a constant distance. We used a road database of a two-lane highway in one direction. While the driver used the automated driving system, he/she conducted SuRT (Surrogate Reference Task [4]) to experimentally introduce visual distraction. The SuRT required the participant to find the target and touch it as quickly and accurately as possible on a touch screen mounted on the dashboard of the simulator. In the easy task condition, the difference in size between target and distractors was greater compared to the difficult task condition.

RtI (Request to Intervene; visual icon and verbal message) was presented during the automated mode. Simultaneously, the automated system ceased to operate. The driver controlled the vehicle manually, and avoided a stopped vehicle appeared in front of the driver’s vehicle. RtI presentation timing was 6 seconds before reaching the obstacle vehicle.

The following evaluation indices were measured in the simulator experiment.

- Brain activity: P2-N1 amplitude for task-irrelevant probes, eye fixation related potentials in small saccade
- Face direction: head movement variability
- Glancing behaviors: percent time of forward looking, percent time of glancing at touch screen
- Eye movements: frequency of small saccade, frequency of large saccade, variability of saccade amplitude, pupil diameter
- Eyelid movements: blinking frequency, blinking duration
- Autonomic nerve: heart rate, blood pressure

The results of the simulator experiment suggest that several indices were sensitive to the difficulty of the SuRT. The number of small saccade was higher in the difficult SuRT condition than that in the easy condition. The proportion of time glancing at front scene was the lowest in the difficult condition among the easy task condition, the automated driving alone condition (no subtask), and the manual driving condition. These two indices suggested the largest differences between in the easy and difficult SuRT conditions, in comparison with the other indices.

The instrumented vehicle was a Tesla Model S equipped with an automated system. 20 drivers (11 females and 9 males, average age: 41.1 years old, average driving experience: 22.2 years) participated in the test course experiment. None drivers participated in the simulator experiment. We used oval road (3200m, 3 traffic lanes, R180m) of the AIST proving ground. The experimental conditions were the same as those in the driving simulator experiment. We used a cone as the obstacle, instead of the stopped vehicle in the simulator experiment. Based on the findings from the driving simulator experiment, we focused on the glancing behaviors and eye movements that could be applied to a driver monitoring system. We have developed a prototype of the driver monitoring system. The system consists of a small camera with more than VGA resolution and with more than 60 fps frame rate. The camera detects high-speed movement of the eyeball when a driver changes the visual target, and a small saccade is defined as 5-8 degrees amplitude and a large saccade is defined as 16-32 degrees amplitude.

The results of the test course experiment suggested similar tendencies to those obtained from the driving simulator experiment. The number of the small saccade was higher during automated driving with the difficult SuRT condition compared to the easy condition. The participants cast their eyes in the frontal direction for a shorter period of time in the higher visual load condition.

The results of the transition behaviors from the automated to manual driving in the driving simulator and test course experiments indicated that the driver's eye-off-road condition before RtI led to a poor stability of driver's manual lateral controls: Standard deviations of vehicle lateral positions within 5 seconds after avoiding the obstacle were higher in the difficult SuRT condition than those in the easy SuRT condition and in the automated driving condition without the SuRT.

Finally, the prototype of the driver monitoring system was evaluated in a real highway environment. The driving route was on Tomei and Shin-Tomei expressways in Japan. Time length of driving was about 3.5 hours per one participant. 42 drivers (18 females and 24 males, average age: 33.5 years old, average driving experience: 14.5 years, non-participation in the simulator and test course experiments) drove the instrumented vehicle (Tesla Model S or Benz E class; both had level 2 automated systems). The drivers conducted a navigation task, instead of the SuRT, which were scale-up and down of the navigation map. In one experimental trip, participants experienced the navigation task about twelve times. RtI was not presented during engaging in the navigation task in the public road experiment.

Figure 1 presents the results of saccade and glancing behavior in the real highway experiment. The number of saccade was higher and the proportion of time glancing at front scene was lower while the participants engaged in the navigation task, suggesting the same results as the driving simulator and test course experiments.

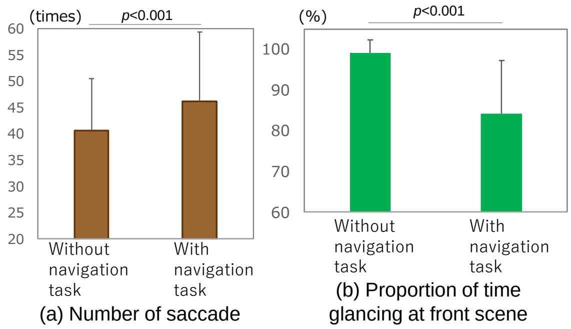

Figure 1. Results of evaluation indices in public roads experiment

References:

[1] SAE International.: 'Taxonomy and definitions for terms related to driving automation systems for on-road motor vehicles', J3016_201806, 2018

[2] Kaplan, S., et al.: 'Driver Behavior Analysis for Safe Driving: A Survey', IEEE Transactions of Intelligent Transportation Systems, 16, (6), pp. 3017-3032

[3] Kitazaki, S., et al.: 'Human Factors and HMI', SIP-adus: Project Reports, 2014-2018 – Automated Driving for Universal Services –, pp. 64-70

[4] ISO/TS 14198: 'Road vehicles – Ergonomic aspects of transport information and control systems – Calibration tasks for methods which assess driver demand due to the use of in-vehicle systems', 2012

Time of day influence on real-time detection of drowsiness and predicted sleepiness

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Keywords: Alertness prediction; Driver monitoring; Drowsiness; Technology development

Background

Video-based driver monitoring systems (DMS) are growing in popularity due to their non-intrusive nature and capacity to capture subtle behavioural changes to detect impaired states such as distraction and drowsiness. The benefit of such technology in reducing risk for professional drivers operating heavy vehicles is now recognised by regulatory bodies and other stakeholders [1]. Historically, risk management for heavy vehicle drivers has focused on limiting hours of service to ensure drivers obtain sufficient rest between shifts. However, it is well documented that fatigue-related driver impairment is highly influenced by circadian sleep-wake cycles [2], [3]; and can be predicted through well-established biomathematical models of fatigue [4]. Hence, combining such predictive models with real-time observation through DMS may provide a more effective method of reducing risk for heavy vehicle drivers whilst allowing scheduling flexibility to ensure both safety and productivity. This extended abstract explores how the predicted probability of sleepiness for heavy-vehicle drivers and DMS-generated real-time ocular indicators drowsiness vary across time of day.

Method

A naturalistic driving study was conducted with an operational trucking fleet as part of the Advanced Safe Truck Concept project (a Cooperative Research Centre Projects-funded partnership program). Ten vehicles were fitted with Seeing Machine's automotive-grade DMS and tracked 102 consenting drivers while they carried out their normal shifts. A total of 425 shifts ranging from 5 - 12 hours in duration were included for analysis. Given that drowsiness is marked by slower eye closure activity, the primary DMS signals selected for analysis were amplitude-velocity ratios (AVR) of eyelid opening and closing [5]. These values were then averaged per 15-minute bins across shift duration.

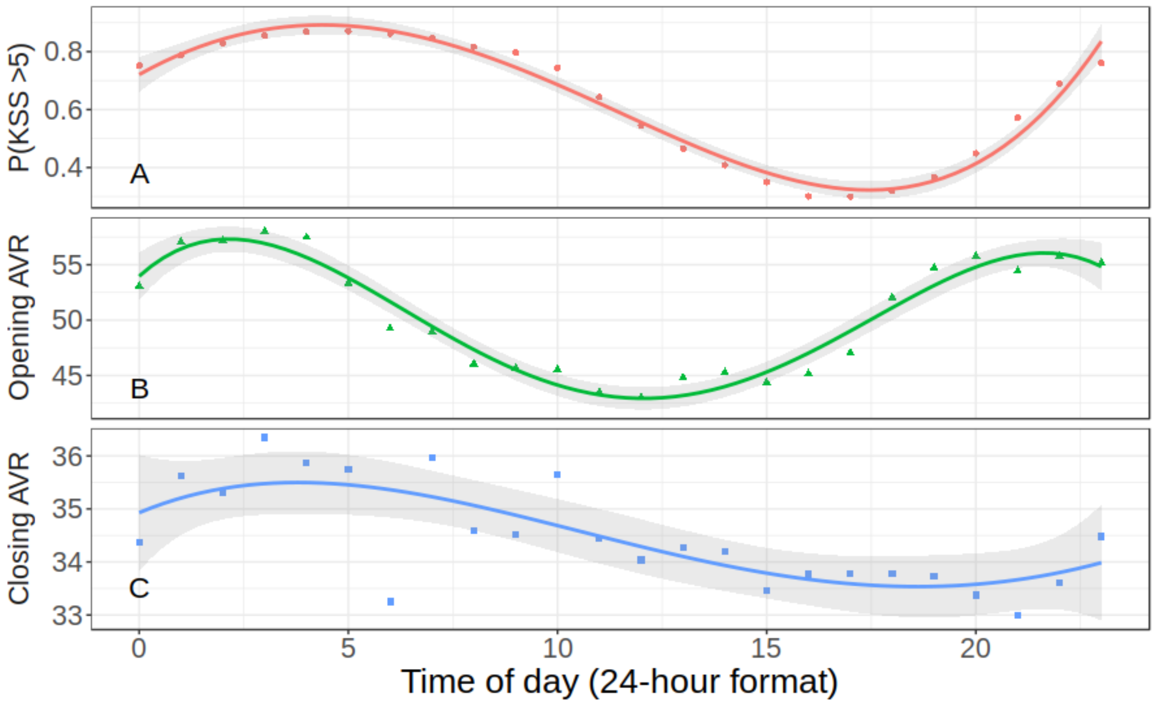
To generate predicted likelihood of sleepiness, the three-process model of alertness was implemented with wake and sleep times set as 2-hours before shift start and 7-hours before wake time, respectively. Predicted alertness scores were generated by 15-minute intervals across shift duration, from which the probability of showing signs of sleepiness as indicated by Karolinska Sleepiness Scale (KSS) scores > 5 was computed. For the purpose of analysis, all values were further averaged into 24 hourly bins across operating time of day.

Results

Probability of sleepiness (KSS >5) varied across time of day and was best fitted by cubic polynomial regression $F_{[4,19]} = 175.7$, $p < .001$, $R^2 = .97$, where there was an increase from 12am - 5am, followed by a decline into the afternoon and an increase from 6pm onwards (see Figure 1A). Similar patterns of variation were observed for opening AVR $F_{[4,19]} = 82.21$, $p < .001$, $R^2 = .93$ whereas closing AVR was better fitted as a linear decline $F_{[1,22]} = 5.66$, $p = .03$, $R^2 = .17$, as depicted in Figure 1B and 1C respectively.

To reduce the potential mitigating effects of rest breaks on the relationship between predicted and observed signs of drowsiness, data from pre-break drive segments were selected. A positive linear relationship was observed between the predicted probability of obtaining KSS > 5 and opening AVR $t_{[22]} = 2.4$, $p = .03$, but the same trend did not reach significance for closing AVR.

Figure 1. Variations in predicted alertness (A) and observed ocular indicators of drowsiness (B & C) across time of day.



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Discussion

There is ample evidence illustrating how physiological and behavioural indicators of driver fatigue are strongly influenced by time of day [2], which was further demonstrated by results from our analysis. As illustrated in Figure 1, the night hours (7pm - 5am) were associated with an increase in predicted likelihood of sleepiness and observed indicators of drowsiness, particularly opening AVR. Although the evidence suggests greater likelihood of drowsiness at night time, it is not realistic to avoid scheduling drivers at such times as fleets have demands to meet. Furthermore, there are additional and less predictable factors that alter alertness at any time of day. Thus, real-time monitoring via DMS in conjunction with risk prediction through these underlying circadian and homeostatic processes that facilitate fatigue onset [4] provides a more cohesive method of predicting, detecting and reducing the risk of drowsy driving.

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References

[1] A. Higginson, D. Dawson, and M. Sprajcer, “Research Report: Phase 2.Fatigue/Distraction detection technology use in the Australian road freight transport sector.” National Heavy Vehicle Regulator, Dec. 2019, [Online]. Available: https://www.nhvr.gov.au/files/202002-1120-phase-2-fatigue-distraction-detection-technology-australia.pdf.

[2] S. I. Kaduk, A. P. J. Roberts, and N. A. Stanton, “The circadian effect on psychophysiological driver state monitoring,” *Theor. Issues Ergon. Sci.*, vol. 0, no. 0, pp. 1–25, Nov. 2020, doi: 10.1080/1463922X.2020.1842548.

[3] H. Zhang, X. Yan, C. Wu, and T. Z. Qiu, “Effect of Circadian Rhythms and Driving Duration on Fatigue Level and Driving Performance of Professional Drivers,” *Transp. Res. Rec.*, vol. 2402, no. 1, pp. 19–27, Jan. 2014, doi: 10.3141/2402-03.

[4] M. Ingre *et al.*, “Validating and Extending the Three Process Model of Alertness in Airline Operations,” *PLoS ONE*, vol. 9, no. 10, p. e108679, Oct. 2014, doi: 10.1371/journal.pone.0108679.

[5] S. Ftouni, S. A. Rahman, K. E. Crowley, C. Anderson, S. M. W. Rajaratnam, and S. W. Lockley, “Temporal dynamics of ocular indicators of sleepiness across sleep restriction,” *J. Biol. Rhythms*, vol. 28, no. 6, pp. 412–424, Dec. 2013, doi: 10.1177/0748730413512257.

Auditory distraction in simulated manual and autonomous driving: an fMRI approach

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Keywords: neuroergonomics, attention, listening, neuroimagery, simulation, car driving

ABSTRACT

It is well known that distraction and inattention can be a contributing factor in driving accidents. In 2018 in France, the road death rate because of distraction and inattention was estimated at 10% [1]. Automation is considered as a solution to mitigate the potential errors of drivers and their consequences. Still, while complete automation is not reached (SAE<5), human should be able to supervise the system and the environment so as to be able to take over the vehicle when required. However, even partial automation can have an impact on drivers' engagement in unrelated driving tasks. Indeed, having fewer driving tasks to manage can make the driver more prone to distraction, notably to fight against boredom. Distractive tasks can then capture part of the driver's attention resources and take him/her away from his/her supervisory task. Consequently, it is important to better understand how people manage to carry out tasks unrelated to driving under both manual and autonomous modes. As no driving activities are required in autonomous mode, a way to assess the impact of distraction in this context is to study how brain activity is modulated by these distractors, using functional magnetic resonance imaging (fMRI). This technique presents the advantage to have a very high spatial resolution allowing to determine accurately the implication of any brain region in specific tasks. This technique has already been used in the last years to study brain activity linked to driving [for example, 2] and to assess the impact of distraction during manual driving [for example, 3, 4].

This project aimed to assess the impact of auditory distraction on the brain activities involved in driving under both manual and autonomous modes. We expected to replicate data from the literature concerning the manual driving and complete these

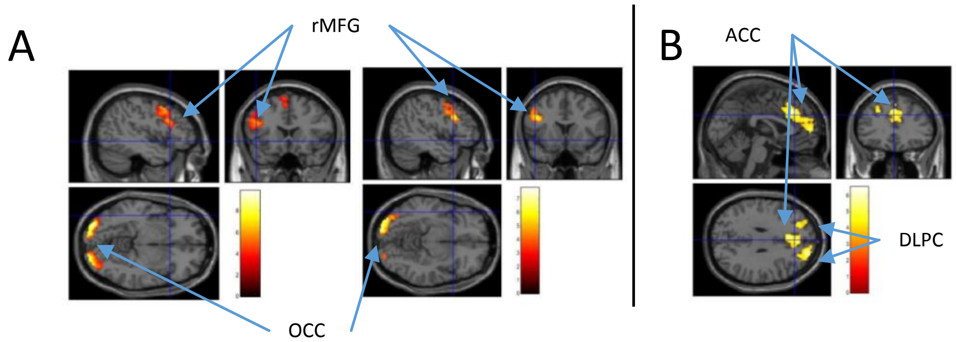
data with what happen in autonomous driving that is when the task is mainly a visual supervision task.

Twenty-five people (aged = 22.8 ± 2.1 year old; 12 men) participated in the study conducted in a MRI 3.0 Tesla (CERMEP, Bron), with a compatible driving simulator. In manual mode, the participant had to follow a vehicle and react by braking whenever vehicle's brake lights were on, using a joystick. In autonomous mode, the simulator reacted automatically. The participants were asked to look at the scene and at the brake lights of the lead car. Each driving task was performed either as a single or as a dual task (listening to a radio broadcast). To ensure that participants were attentive to the radio broadcasts, three questions were asked at the end of the each scenario.

The protocol consisted in 4 runs of about 10 minutes each: 2 runs in autonomous mode (A) and 2 runs in manual mode (M). The 4 runs were counterbalanced among the participants to avoid training or fatigue effect. Each run consisted in 4 blocks: 2 in single task (silence, S) and 2 in double task (listening, L). This leads to 4 conditions (AS, AL, MS, ML) which were repeated 4 times. A block consisted in a driving task for 90 sec followed by questions (about 30 sec) either on the broadcast after condition L or on the thoughts of the participant after condition S. Questions were followed by 30 sec rest periods (R) where participants had only to look at the visual static scene.

fMRI analysis have been conducted with SPM12 (FIL, WTCN, London). A first level analysis was performed for each participant for the contrasts corresponding to the 4 conditions versus the rest condition using the general linear model (GLM) (MS>R, ML>R, AS>R, AL>R). A second level analysis (group analysis) was performed including the previous results from all the participants to study: firstly, the mentioned contrasts (by using one sample t-tests); and secondly, the comparisons between conditions (MS>ML, AS>AL, ML>MS, AL>AS) (by using Student t-test). Multiple comparison correction was applied (Family-Wise Error method) with a threshold of $p < .05$.

Figure 1. A. Contrasts MS>R and AS>R showing activation in the occipital regions (OCC) and in the right middle frontal gyrus (rMFG). B. Contrast MS>ML, showing a different activity in the bilateral dorsolateral prefrontal cortex (DLPC) and in the anterior cingulate cortex (ACC) between both conditions.



The results show similar activation patterns in manual and autonomous conditions in single task (Figure 1A), with a significant activation within the middle frontal gyrus, implied in executive attention, sensory-motor activities, ocular movements and supervision [5], and within the occipital regions, reflecting the visual processing.

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Compared to the single task and as expected, the dual task increases the activity of the regions associated with auditory-verbal comprehension within the auditory cortex, whatever the driving mode. In addition, in manual driving, the dual task decreases the activity of the regions that can be associated with driving management (bilateral dorsolateral prefrontal cortex and anterior cingulate cortex), since these regions are usually associated with executive control, attention and error control (Figure 1B). In contrast, this effect was not significant when listening under the autonomous mode (AL vs AS).

In conclusion, in this study the brain activities related to the driving task are similar in manual and autonomous mode. This similarity can be explained, at least partially, by the simplicity of the driving task used (simple following task) in a simple driving context (no intersection, no traffic). Further research by implementing more complex driving situations as well as more engaging dual task are needed to confirm these phenomena. Regarding the impact of the dual task, the decrease of activities in frontal regions in manual mode with dual task is in agreement with the literature [3, 4] and supports the interpretation that less resources are available to process the visual scene. The absence of such effect in autonomous driving context may be due to the fact that attentional resources in autonomous mode may be similar in single and dual task. It is known that mindwandering is stronger in monotonous situations, as in the autonomous mode when no secondary is asked. It is plausible that the attentional demand of mindwandering (attention focused on self thoughts in single task) and listening (attention focused to the broadcast in dual task) is similar in our context.

As long as drivers have to resume control from time to time, it is important to be aware of the extent to which competing tasks and mindwandering can affect information processing and thus situational awareness. To our knowledge, this study is the first one to look at how a driver manages auditory distraction in an autonomous driving context using fMRI. This is only a first step and further studies are needed that vary the mental workload and the cognitive demand of competitive tasks and mindwandering.

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References:

[1] ONISR2018: Accidentalité routière 2017- résultats définitifs, ONISR, Paris, France, 9p.
[2] Choi, M.H., Kim, H.S., Yoon, H.J., et al.: ‘Increase in brain activation due to sub-tasks during driving: fMRI study using new MR-compatible driving simulator’. J. Physiol. Anthropol., 2017, 36(1), 11.
[3] Hsieh, L., Young, R. A., Bowyer, S. M., et al.:’Conversation effects on neural mechanisms underlying reaction time to visual events while viewing a driving scene: fMRI analysis and asynchrony model’. Brain Res., 2009, 1251, 162-175.
[4] Schweizer, T. A., Kan, K., Hung, Y., et al.: ‘Brain activity during driving with distraction: an immersive fMRI study. Front. Hum. Neurosci., 2013, 7, 53.
[5] Andersson, M., Ystad, M., Lundervold, A., Lundervold, A. J. :’ Correlations between measures of executive attention and cortical thickness of left posterior middle frontal gyrus - a dichotic listening study. Behav. Brain Funct., 2009,5, Article 41.

Painting the bigger picture given by psychophysiological measures: A cognitive load driving study that acknowledges side effects of repetition and traffic scenario

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Keywords: Cognitive load; Driver distraction; Psychophysiological measures; Test methodological side effects; Traffic environment

INTRODUCTION

Effects of cognitive load on traffic safety are debated and unclear [1] and reliable measurements of cognitive load are sought. Physiological measures are of interest because they can provide continuous and more or less non-invasive recordings. Those can complement, extend and/or substitute behavioural and self-reported measures to improve assessments of cognitive load, as well as other driver states [2], [3]. Several physiological measures have been shown to respond to cognitive load manipulations [3]–[6].

Most studies of driving under cognitive load assign differences in driving performance and physiological responses solely to the different levels of cognitive load to which the drivers are exposed. Consequently, how potential side effects of cognitive load manipulations (e.g. emotional stress caused by the test situation) and traffic context (e.g. the driving scenarios used) might affect drivers' responses are generally overlooked. By ignoring such factors, one risks making erroneous generalizations from the results [7]. However, because changes in physiological measures can have many different causes [2], their similarities and dissimilarities contain valuable information about the driver state. The aim of the present study is therefore to analyse drivers' physiological responses during driving not only in relation to levels of cognitive load, but also in relation to scenario repetition (associated with emotional stress caused by task novelty [8]) and in relation to different traffic scenario types.

METHOD

72 participants drove approximately 40 minutes each on a simulated rural road in a moving-base driving simulator. The route included two intersection scenarios selected for further study; one where the participants, having right of way, passed through a four-way intersection with a potential conflict vehicle approaching from the right, and another where they passed by a hidden exit. Each scenario was repeated four times. When driving through these scenarios the participants were either involved in a simple cognitive task (1-back), a more difficult cognitive task (2-back) or not doing any task besides driving (No Task). The cognitive tasks were one minute long and the time segment from 10 to 60 seconds after task onset was used in the statistical analysis.

From the recorded physiological data, heart rate (HR), standard deviation of RR-intervals (SDRR), eye blink rate (BR), eye blink duration (BD), respiration rate (RR), skin conductance (SC) and pupil diameter (PD) were derived. Signals and derived measures were visually inspected and unreliable segments were excluded from the analysis. Participants were only included in the analysis if they had data of sufficient quality in all four repetitions of a scenario.

To test for effects of cognitive load (No Task, 1-back and 2-back) and repetition (1 to 4), Mixed Model ANOVAs and subsequent Bonferroni post hoc corrections were performed. Participant was included as a random factor.

RESULTS

Eight participants were excluded from the analysis due to simulator sickness or logging issues. After the visual inspection of the physiological signals and derived measures, the number of participants included in the analyses was 61/62 (hidden exit/four-way intersection) for HR and SDRR, 50/49 for BR and BD, 47/41 for RR, 53/52 for SC, and 35/39 for PD.

Cognitive load had a significant effect on all measures in both traffic scenarios (see hidden exit in Figure 1), except on BD in the four-way intersection scenario. The effect was most consistent for PD, which had significant differences between all load levels in both traffic scenarios. HR, SDRR and RR all showed highly significant differences for drivers under cognitive load compared to when not under load but were less good at differentiating between levels of load (i.e. the 1-back and 2-back tasks).

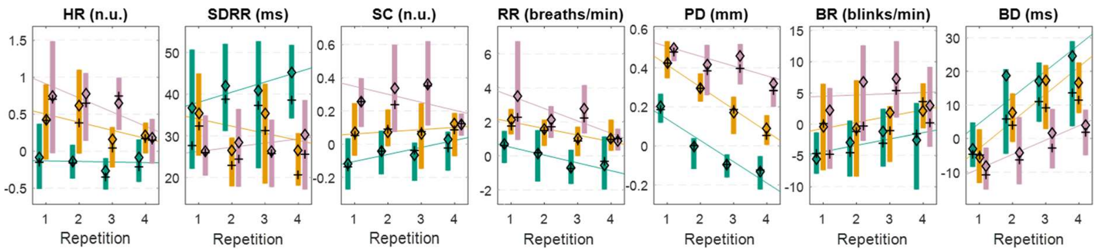

Figure 1. Effects of cognitive load and repetition in the hidden exit scenario. Green represents No Task, orange 1-back, and purple 2-back. Lines are least-square lines. Black diamonds are mean values and crosses median values. Boxes goes from 25th to 75th percentiles. All signals have been normalized to compensate for individual differences. HR is Z-normalized, the SC signal is normalized on absolute level using the time interval 70 to 10 seconds prior to the analysis segment and on individual response amplitude, and the other signals are baseline adjusted by subtraction of the entire signal's median value. n.u. = normalized units.

Scenario repetition had a significant effect on HR, PD, RR and BD in both scenarios. Interestingly, for HR the effects of repetition only occurred under cognitive load (HR levels decreased when scenarios were repeated) but there was no change in the No Task condition. In other words, the initial effect of cognitive load on HR attenuated with repetition. In contrast, PD decreased with repetition in all conditions and the difference between conditions remained.

Traffic scenario had different effects on different measures. As the traffic environment complexity increased, i.e. when the driver approached the hidden exit or four-way intersection, PD and SC increased while BR and BD decreased (see Figure 2). For HR, a decrease can be seen after passing the hidden exit in the load conditions. No traffic scenario effects are evident in RR.

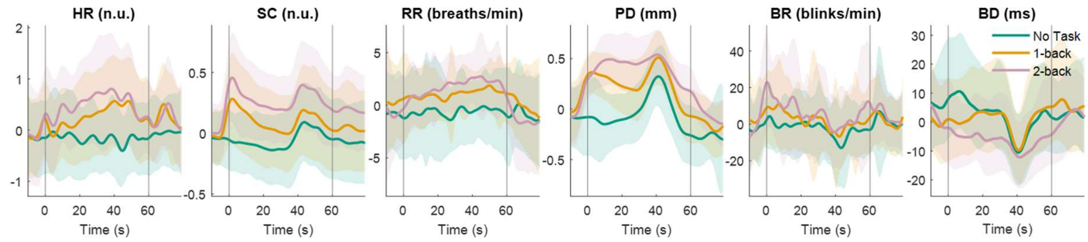

Figure 2. Continuous plots over each measure in the hidden exit scenario (all repetitions). The cognitive tasks start at time 0 (first vertical line) and lasts for 60 s (second vertical line). A few seconds before time 0 participants are informed that the task will soon begin. The participants reach the hidden exit around time 45 s. The thick lines are the mean values, except in BD where it is the median. The shaded areas are ±1 standard deviation, except in BD where it covers the area from the 25th to the 75th percentile. Signals are normalized as described in the Figure 1 caption and smoothened for clearer visualization.

DISCUSSION

In line with previous research, cognitive load had significant effects on all physiological measures [3]–[6]. However, there were also clear differences between the measures when analysing the effects of traffic scenario and scenario repetition.

For one, the results clearly show that physiological responses to variations in cognitive load may not only represent a response to the load in itself but also capture side effects caused by the experimental setting [7]. For example, while the effect of cognitive load on PD remained consistent in all repetitions, the effect on HR attenuated with repetition. This is probably due to the fact that while PD has a close physiological relationship to cognitive attention and effort [9], HR is more sensitive to arousal and stress [2], [10]. The HR measure thus indicates that participants became more relaxed over time when performing the cognitive tasks, while the PD metric suggests that they still invested the same amount of cognitive effort in performing them.

The study also highlights the fairly intuitive insight that drivers' cognitive states are not constant. Rather, cognitive states changed both over time and in response to traffic scenario variations. A clear illustration of this can be seen when the drivers approached the intersections. PD then increased, reflecting an increase in cognitive effort [9], while BR decreased, revealing an increase in visual attention [11], [12]. That is, as the drivers approached the intersections, they increased their cognitive load by paying more attention to the traffic environment.

When generalizing experimental results to other contexts, test methodological side effects and contextual influences need to be carefully considered. Side effects, such as emotional stress caused by the experimental setting, can significantly influence both physiological responses [13] and driver behaviours [14]. In real life situations, where drivers themselves choose how, when and where to engage in cognitively loading tasks, such side effects might not be the same. Likewise, contextual variations, such as traffic environmental changes, can also affect both physiological measures and driver behaviours and lead to incorrect conclusions if not properly accounted for. Instead of only viewing multiple physiological measures as "backups" for each other in unidimensional analyses [3], [15], it is therefore also worth studying their similarities and differences in multiple dimensions to get a more nuanced view of the driver state. Viewed in this more holistic way, psychophysiological measures can likely take on a more prominent contributing role in our understanding of how cognitive states relate to crash causation and prevention than they historically have done.

REFERENCES

[1] K. P. Wijayaratna, M. L. Cunningham, M. A. Regan, S. Jian, S. Chand, and V. V. Dixit, "Mobile phone conversation distraction: Understanding differences in impact between simulator and naturalistic driving studies," *Accid. Anal. Prev.*, vol. 129, no. May, pp. 108–118, 2019.

[2] G. Matthews, L. E. Reinerman-Jones, D. J. Barber, and J. Abich, "The psychometrics of mental workload: Multiple measures are sensitive but divergent," *Hum. Factors*, vol. 57, no. 1, pp. 125–143, 2015.

[3] M. Lohani, B. R. Payne, and D. L. Strayer, "A review of psychophysiological measures to assess cognitive states in real-world driving," *Front. Hum. Neurosci.*, vol. 13, no. March, pp. 1–27, 2019.

[4] A. M. Brouwer, M. A. Hogervorst, M. Holewijn, and J. B. F. van Erp, "Evidence for effects of task difficulty but not learning on neurophysiological variables associated with effort," *Int. J. Psychophysiol.*, vol. 93, no. 2, pp. 242–252, 2014.

[5] G. Marquart, C. Cabrall, and J. de Winter, "Review of Eye-related Measures of Drivers' Mental Workload," *Procedia Manuf.*, vol. 3, pp. 2854–2861, 2015.

[6] B. Mehler, B. Reimer, and J. F. Coughlin, "Sensitivity of physiological measures for detecting systematic variations in cognitive demand from a working memory task: An on-road study across three age groups," *Hum. Factors*, vol. 54, no. 3, pp. 396–412, 2012.

[7] M. Richter and K. Slade, "Interpretation of physiological indicators of motivation: Caveats and recommendations," *Int. J. Psychophysiol.*, vol. 119, no. January, pp. 4–10, 2017.

[8] R. M. Kelsey, K. Soderlund, and C. M. Arthur, "Cardiovascular reactivity and adaptation to recurrent psychological stress : Replication and extension," *Psychophysiology*, vol. 41, pp. 924–934, 2004.

[9] P. van der Wel and H. van Steenbergen, "Pupil dilation as an index of effort in cognitive control tasks: A review," *Psychon. Bull. Rev.*, vol. 25, no. 6, pp. 2005–2015, 2018.

[10] C. Dussault, J. C. Jouanin, M. Philippe, and C. Y. Guezennec, "EEG and ECG changes during simulator operation reflect mental workload and vigilance," *Aviat. Sp. Environ. Med.*, vol. 76, no. 4, pp. 344–351, 2005.

[11] M. Á. Recarte, E. Pérez, Á. Conchillo, and L. M. Nunes, "Mental Workload and Visual Impairment: Differences between Pupil, Blink, and Subjective Rating," *Span. J. Psychol.*, vol. 11, no. 2, pp. 374–385, 2008.

[12] V. Faure, R. Lobjois, and N. Benguigui, "The effects of driving environment complexity and dual tasking on drivers' mental workload and eye blink behavior," *Transp. Res. Part F Traffic Psychol. Behav.*, vol. 40, pp. 78–90, 2016.

[13] D. Conway, I. Dick, Z. Li, Y. Wang, and F. Chen, "The effect of stress on cognitive load measurement," in *Human-Computer Interaction INTERACT 2013. Lecture Notes in Computer Science*, 2013, vol. 8120, pp. 659–666.

[14] G. C. Gotardi *et al.*, "Adverse effects of anxiety on attentional control differ as a function of experience: A simulated driving study," *Appl. Ergon.*, vol. 74, no. August 2018, pp. 41–47, 2019.

[15] D. Tao, H. Tan, H. Wang, X. Zhang, X. Qu, and T. Zhang, "A systematic review of physiological measures of mental workload," *Int. J. Environ. Res. Public Health*, vol. 16, no. 15, pp. 1–23, 2019.

Uncovering driver inattention and distraction in fatal and injury crashes

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Keywords: Inattention, distraction, in-depth crash investigation, systems approach

ABSTRACT

Introduction

Research has demonstrated that distraction and inattention can lead to diminished driving performance [e.g. 1, 2] but there is limited evidence regarding their role in crashes. Investigating the role of distraction within crashes, and the context within which it occurs, is challenging as it is often difficult to obtain accurate information about circumstances preceding a crash. The in-depth analysis of crashes which includes participant interviews is likely to elicit more information about pre-crash circumstances and motivations due to the assurance of confidentiality, lack of legal consequences and ability of the interviewer to prompt the participant. Importantly, it also permits the investigation of underlying behavioral mechanisms behind inattention-related crashes (e.g. cognitive distraction) that might not be revealed using other methods. This study investigated the contribution of driver distraction and inattention within a sample of fatal and injury crashes using recent in-depth road crash investigation data. The wider context in which inattention-related crashes occurred was also examined to assist in developing system-based solutions.

Method

The sample included in-depth crash data from 186 fatal and injury crashes in South Australia investigated from 2014-2018. Within the sample, there were 259 drivers/riders (drivers n=225, motorcycle rider/cyclist n=34). Crash case notes were reviewed to determine if there was evidence that attentional failures contributed to the crash. A standard definition of inattention and distraction was operationalised in order to code the data. Using an adapted taxonomy of inattention [3], five subtypes of driver inattention were defined: misprioritised attention, neglected attention, cursory attention, diverted attention (distraction) and unspecified inattention. The characteristics of inattention crashes were also compared with those for non-inattention-related crashes.

Results

Of the 160 crashes for which there was sufficient information, 31.3% showed evidence of driver inattention contributing to the crash. A summary of the prevalence of inattention and

distraction in crashes by subtype is presented in Table 1. The most common subtypes of inattention were distraction (13.8% of all crashes) and driver misprioritised attention (8.1%). The distraction-related crashes included a variety of different distractions with those located in-vehicle the most prevalent (e.g. phone use, passenger interaction, searching for objects), followed by internal thoughts (e.g. emotional stress) and external behaviours (e.g. other road users). Distraction from phone use was identified in 2.5% of all crashes (18% of distraction crashes). The majority of distractions were cognitive (64%) and voluntary (77%) in nature.

Table 1: Prevalence of inattention and distraction in crashes by subtype

Inattention subtype	Number of crashes (n=50)	Percentage of inattention crashes	Percentage of crashes coded within taxonomy (N=160)
Driver misprioritised attention (DMA)	13	26.0%	8.1%
Driver neglected attention (DNA)	3	6.0%	1.9%
Driver cursory attention (DCA)	6	12.0%	3.8%
Unspecified inattention (U)	6	12.0%	3.8%
Driver diverted attention (DDA - Distraction)	22	44.0%	13.8%
Internal	7	(14.0%)	(4.4%)
Task related thoughts	(3)		
Emotional/stressed	(3)		
Task unrelated thoughts	(1)		
In-vehicle [a]	12	(24.0%)	(7.5%)
Using mobile phone	(4)		
Passenger interaction	(3)		
Adjusting/searching for object	(3)		
Looking down	(1)		
Animals in vehicle	(1)		
Music (headphones)	(1)		
External	3	(6.0%)	(1.9%)
Other road user behavior	(3)		

[a] One crash had two in-vehicle distractions; subtypes of in-vehicle distractions do not sum to 12.

In comparison to non-inattention crashes, inattention crashes were statistically significantly more prevalent in metropolitan areas (78%), occurred more frequently at intersections (60%) and on roads with a speed limit of 60km/h or lower (74%). Analysis of crash types indicated that inattention crashes were most commonly right turn/angle crashes (44%) followed by rear end crashes (16%) while crashes not involving inattention were most frequently single vehicle crashes (47%).

Analysis of the demographic characteristics of the 259 drivers indicated that 23.2% (n=22) of females were inattentive compared to 17.1% (n=28) of males but this difference was not statistically significant. Around 36% (n=18) of inattentive drivers were younger, aged 16–29years, in comparison to 23% (n=47) of drivers who were not inattentive, and this difference was statistically significant (X^2=3.8, df=1, p=.05).

Conclusions

This study established that almost a third of fatal and injury crashes involved driver inattention and distraction and many of these crashes could have been prevented. This proportion was of a similar magnitude to that found in a recent study of fatal crashes in Norway [4]. System-wide solutions that could mitigate or prevent inattention and distraction crashes include intervening vehicle safety technologies, infrastructure solutions to provide a forgiving road environment, blocking capabilities within technologies to prevent communications while driving and interventions communicating the risks associated with inattention. Of significance, this study also demonstrated the importance of in-depth data for understanding the contribution of distraction and inattention in crash causation.

Acknowledgments

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References:

[1] Klauer, S., Guo, F., Simons-Morton B., Ouimet M., et al.: ‘Distracted driving and risk of road crashes among novice and experienced drivers’, N. Eng. J. Med., 2014, 370 (1), pp. 54-59.

[2] Harbluk, J., Noy, Y., Trbovich, P., Eizenman, M.: ‘An on-road assessment of cognitive distraction: Impacts on drivers’ visual behavior and braking performance’, Accid. Anal. Prev., 2007, 39 (2), pp. 372-9.

[3] Regan, M., Hallett, C., Gordon, C.: ‘Driver distraction and driver inattention: Definition, relationship and taxonomy’, Accid. Anal. Prev., 2011, 43 (5), pp. 1771-81.

[4] Sundfør, H., Sagberg, F., Høye, A.: ‘Inattention and distraction in fatal road crashes– Results from in-depth crash investigations in Norway’, Accid. Anal. Prev., 2019, 125, pp. 152-157.

Strategies used by young male drivers for coping with driver boredom

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Keywords: boredom, coping strategies with boredom, driver boredom, traffic safety.

ABSTRACT

Through our work we decided to focus on the, still relatively new, topic of driver boredom. As the main aim of our study we established the collection of as many of the strategies used by drivers to cope with boredom behind the wheel, as the circumstances allowed. In order to reach this ultimate goal, we have set ourselves several other partial goals, that are mentioned further.

The first step taken was a thorough examination of existing previous research on the topic of boredom itself. Through this action we managed to compare several different theoretical approaches both to the boredom in general and to the driver boredom specifically. Based on this theoretical research, we chose to view boredom through the scope of Mihaly Csikszentmihalyi (2000) and his concept of optimal stimulation, widely known as flow. Therefore, we perceive driver boredom as a state of either under- or overstimulation, in other words as a state, that is not a flow. We chose this point of view because of it seeming to be the most appropriate for the driving environment, where one can get bored both by driving down an empty speedway in the middle of the night (understimulation) and by crawling through the heavy city traffic (overstimulation).

As we have mentioned above, through our research we mainly focused on finding and describing as many of the coping strategies, as possible. In order to achieve our goal, we have set ourselves six research questions in total, that were following: (RQ1) What strategies are used by drivers in order to not get bored while driving?; (RQ2) Which of those strategies are perceived by drivers as safe, if any (is there some strategy, that is perceived by one driver as safe, perceived as dangerous by others)?; (RQ3) In what situations does the driver get bored?; (RQ4) Approximately after what period of time does the driver get bored?; (RQ5) What strategies are used by the drivers in the overstimulating environment?; (RQ6) What strategies are used by the drivers in the understimulating environment?

With the need to really get to know the topic of coping with boredom, that arose from our research questions, we have decided to conduct our work in the form of descriptive research. In order to get a maximum amount of possible answers to our research questions, we chose mixed design of the research. Therefore, the work can be divided into two parts.

The first part was an exploratory qualitative semi-structured interview, through which we mainly tried to further understand the fundamentals of the topic. The interview consisted of 17 questions. In an order to at least basically understand to the driving style (mainly to their tendency to disobey the law and to the erroneous driving) of the interviewed drivers, we also administered them with the Driving Behavior Questionnaire (Šucha, Šrámková & Risser, 2014). Then we moved to the second part of the research. Based on the answers gained through our interviews, we have created a questionnaire, consisting of 11 closed-ended questions, that was meant to extend the findings of the interviews as much as possible.

Regarding our research sample, we have chosen to work with male drivers in the age between 18-25 years. We opted for this particular population, since it is not only with no doubt the most dangerous group of drivers, as proved by numerous studies (Brown et al., 2017), but also appears to be the most boredom prone group (Sundberg et al., 1991). 225 young male drivers participated in our study in total. 14 of them did so through the interviews and Driving Behavior Questionnaire (mean age 23.0 years; SD = 1.36), they were found through the method of snowball sampling. Remaining 211 drivers participated via the questionnaire (mean age 22,93; SD = 1,92). The questionnaire respondents were found online, with the help of Facebook, recruited mainly from the groups of fans of specific automobile brands. All of the obtained data were anonymous. For both the interview and the questionnaire, we asked drivers only about their age, for Driving Behavior Questionnaire we asked about age and gender.

Through our research we managed to collect 45 coping strategies in total. Initially we wanted to divide them into two categories (*approach* and *avoidance*), as used by Steinberger, Moeller & Schroeter (2016), but then we decided to aim for a finer, more specific sorting. Therefore, we divided strategies into 11 thematic categories. On the following lines we present those categories in descending order, in terms of how many times was the given category mentioned. For each category we mention a few of the specific strategies.

The most frequent category was *music*, which our drivers reported more than twice as much, than the remaining categories. Drivers mentioned for example listening to music, singing, or tapping the rhythm of the song on the steering wheel. Second category was *passenger*, where drivers mentioned, besides the rather obvious conversation, also playing simple games with the passenger, while for others the simple presence of the passenger was enough of a "strategy" as well. *Thinking* happened to be our third category, where for instance mind wandering but also mindfulness was mentioned. Fourth category was *driving style*, represented by fast driving, but also by focusing on advance driving techniques, or by aggressive driving. *Consumption*, as our fifth category, mainly consisted of smoking, drinking and eating. Sixth category was *Observation*, where drivers mainly just looked around, but also for example specifically focused on cars passing by, or on women on sidewalks. *Spoken word*, seventh category, was represented by podcasts, radio shows, audio books or preachments. Eighth category was *mobile phone/smartphone*, which we anticipated to appear more often, consisted of making phone calls, sending sms or even playing with the phone. *Control features*, nineth category, where drivers mentioned pushing buttons, moving levers, or even shifting in and out of gear just for the sake of it, or adjusting one's seat. Last but one category was a specific one, which we labeled as *completely evasive*. Drivers were mentioning even sex or watching movies. Final category was *route alternation*, which we found quite innovative and consists of taking short breaks or even altering or changing the route in order to make it more interesting and less boring.

Regarding the subjective safety of obtained strategies, listening to the music was perceived as the safest one, while playing with the phone was considered to be the most dangerous one. However, as we asked the drivers about their formal experience with the use of those strategies in real life, looking around seemed to be the most dangerous strategy overall.

Further, we found altogether 17 factors, that caused boredom of our drivers. We mention those in the same order, as the coping strategies – from the most mentioned one to the least mentioned one. The factors were monotony, waiting, well-known route, long route, speedway, being in a car alone, specific situation (e.g. early in the morning, driving in dark, driving in rain, driving in sunset, driving after having a meal), disruption of one's tempo, specific car (e.g. car not being entertaining enough, car not being powerful enough, car being equipped with ADAS).

When we focused on the time, after which the driver starts to get bored, we assumed, that young male driver will be bored in matter of minutes after sitting behind the wheel. However, results of our research indicate something else. Average representant of our research sample reported to start feeling boredom after 64,43 minutes (SD = 73,25), therefore, based on our research, we can state that young men often don't get bored behind the wheel, until the first hour of driving passes.

The last finding of our study relates to the last two of our research questions, that is the difference between under- and overstimulating environment in relation to coping strategies. To our surprise, we found no significant difference in strategies used in those specific environments.

Through our research most of all we wanted to describe the complex situation regarding the driver boredom and coping strategies of young drivers. Therefore, the whole research is a sort of summary of the topic, with the main focus on the coping strategies, their functionality and their impact on the traffic safety.

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References:

[1] Csikszentmihalyi, M. (2000). *Beyond boredom and anxiety*. Jossey-Bass.
[2] Sucha, M., Sramkova, L., & Risser, R. (2014). The Manchester driver behaviour questionnaire: self-reports of aberrant behaviour among Czech drivers. *European transport research review*, *6*(4), 493.
[3] Brown, T. G., Ouimet, M. C., Eldeb, M., Tremblay, J., Vingilis, E., Nadeau, L., ... & Bechara, A. (2017). The effect of age on the personality and cognitive characteristics of three distinct risky driving offender groups. *Personality and individual differences, 113*, 48-56.

[4] Sundberg, N. D., Latkin, C. A., Farmer, R. F., & Saoud, J. (1991). Boredom in young adults: Gender and cultural comparisons. *Journal of Cross-Cultural Psychology*, *22(2), 209-223.*
[5] Steinberger, F., Moeller, A., & Schroeter, R. (2016). The antecedents, experience, and coping strategies of driver boredom in young adult males. *Journal of safety research*, 59, 69-82.

Sleep in Automated Driving – The Perception of Sleep Inertia after Take Over

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Keywords: Affinity Diagram, Automated Driving, Driver State, Sleep Inertia, Take-over Performance.

Increasing vehicle automation gradually changes the driver's role during driving. While in partially automated driving (AD) the driver is required to monitor the driving constantly, in higher automation levels she can withdraw completely from the driving task and is only needed to intervene occasionally (see e.g. the SAE taxonomy of vehicle automation [1]). The role of the driver is similar to the role of a pilot flying in autopilot mode who is only required to intervene in unusual circumstances or for special tasks like e.g. takeoff and landing. By SAE level 4 (L4) the driver will be enabled to sleep during the automated drive, however, she will still have the possibility to drive manually. This circumstance raises the question whether after sleeping a driver is able to perform the driving task.

Sleep Inertia (SI), the "*period of transitory hypovigilance, confusion, disorientation of behavior and impaired cognitive and sensory-motor performance that immediately follows awakening*" [2] is a well-investigated phenomenon in the field of aviation, where pilots are allowed to sleep during the flight and after sleep return to duty.

With the upcoming of AD drivers will increasingly be at risk of sleeping behind the (automated) wheel and even voluntarily do so. It is therefore important to understand if and how SI impacts drivers' performance in the period after sleep. The aim of the presented study is to gain a first insight in drivers' subjective perception of driving under the influence of SI.

A study with N = 19 drivers was conducted in a high-fidelity driving simulator where participants could use an L4 automated motorway chauffeur during 6 drives with the aim to investigate naturalistic behavior. One drive took place at 6 a.m. after participants were allowed a maximum of 4 hours of sleep in order to investigate their behavior in the state of sleepiness. N=7 drivers fell asleep during the drive after sleep deprivation which was confirmed by an expert scoring sleep according to the AASM standard using EEG [3]. When sleep was confirmed, a take-over request (TOR) was issued urging drivers to take back the vehicle control. The TOR was an auditory alarm along with a displayed notice that the AD mode would end soon. After take-over, drivers were exposed to one of two driving situations: The first situation was a monotonous 10-minute drive on a 3-lane motorway with low traffic volume during rain. The drivers' main task was to keep the vehicle in its lane and to keep the speed limit of 120 km/h. The second situation was a roadwork site where drivers had to change lanes to avoid an obstacle.

After the drive, those participants who had experienced at least one take-over situation after sleep took part in a semi-structured narrative interview with the aim to gain a deeper understanding of their subjective perception of driving under the influence of SI.

The main interview questions were: 1) "Please describe your condition and your driving behavior after sleep." and 2) "Please compare the process of waking up due to a take-over request to waking up from your alarm clock in the morning."

The interviews were recorded and then analyzed with the Affinity Diagram, a contextual design method [4]. The Affinity Diagram is a bottom-up method to find a structure in data. The interviewees' statements are written down on post-it stickers in a workshop session stickers are grouped according to similarities in the statements (see Figure 1, "yellow level"). Then titles are given for each group ("blue level"). Those titles are then again grouped to higher categories ("red level") and overall top-level categories are built ("green level").

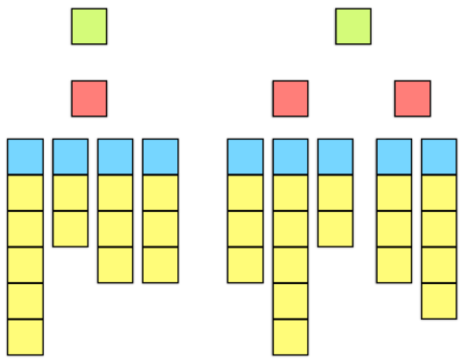

Figure 1: Basic structure of an Affinity Diagram

The Affinity Diagram yielded 3 main categories with 5 categories of impacts of prior sleep on driving. One level below 14 subcategories were found. Categories, subcategories and examples of statements for each subcategory are listed in Table 1.

Table 1: Categories resulting from the Affinity Diagram.

Level 1	**Level 2**	**Level 3**	**Example statements**
Performance impairments	Impairments in Driving behavior	Impaired lane-keeping	"I had the impression that after taking over, my lane-keeping was really bad"
		Impaired speed keeping	"It was not easy for me to keep the speed. Sometimes it was 5 km/h too low, sometimes 10 km/h too high."
		Insecurities in driving	"I felt very insecure behind the wheel."
		Cautious driving	"I tried to stay on the right lane in case something might happen."

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Level 1	Level 2	Level 3	Example statements
	Cognitive & Behavioral Impairments	Slower reaction	“My reaction was way too late.”
		Lower attention	“I had the feeling I drove really bad and that I was very inattentive.”
		Difficulties to concentrate	“I had difficulties to really concentrate on the driving task and stay focused.”
		Impaired perception	“I realized too late that there was a road sign”
Negative affect	Lower motivation	Reluctance to drive	“I have had enough of driving drowsy.”
		Desire to relax	“I was waiting for the autopilot to be available again so that I could continue to sleep.”
	Emotional stress	High strain	“I had to make on effort not to fall asleep again.”
		Numbness	“I didn’t feel fit at all.”
Physical symptoms	Physical symptoms	Eye problems	“I blinked more frequently and touched my eye.”
		Headache	“I got a bad headache.”

To summarize, three main manifestations of SI were found during driving: Performance impairments, negative affect and physical symptoms. Those findings have to be taken into consideration when designing automated vehicles that offer both the option to sleep in automated mode and the option to drive manually. Performance impairments after sleep are especially relevant for driving safety. The negative affect as well as the physical symptoms might decrease drivers’ acceptance of AD. SI should be taken into account when designing AD vehicles that allow the driver to sleep.

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References:

[1] SAE: ‘Taxonomy and Definitions for Terms Related to Driving Automation Systems for On-Road Motor Vehicle’, 2018.
[2] Ferrara, M., De Gennaro, L.: ‘The sleep inertia phenomenon during the sleep-wake transition: theoretical and operational issues’, Aviation, space, and environmental medicine, 2000, 71(8), pp. 843-848
[3] AASM: ‘The AASM Manual for the Scoring of Sleep and Associated Events: Rules, Terminology and Technical Specifications’, 2017, American Academy of Sleep Medicine, Darien, IL.
[4] Holtzblatt, K., Beyer, H.: ‘Contextual Design. Sythesis Lectures on Human-Centered Informatics’ in. Carroll, J.M., 2014, Penn State: Morgan & Claypool.

The longer the autonomous phase, the greater impact on driver's take over behavior?

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Keywords: Take-over request, Driver behavior, Long durations, Non-critical event, Simulating level 3 automation.

ABSTRACT

Numerous studies have shown that driving on highway for long durations induces drowsiness and lack of attention ([1], [2]), which is a result of the monotonous travel environment (i.e. low traffic density). As a response, car manufacturers are developing "Highway chauffeur" conditional functions, designed for long automated travel at high speed. The main goal is to allow the driver to devote travel time to non-driving related tasks such as working, watching movies, or reading among other things. It is particularly relevant to remember that "conditional" means the driver must be able to regain control at each instant, whatever his/her state or travel environment (i.e. traffic density). However, it is now well-known that an "out-of-loop state" could be induced by such periods of autonomous driving, particularly if one considers long periods of automation ([2], [3]). This issue represents a major problem that manufacturers must better understand to safely develop this function. To add new insight to the factors inducing the "out-of-the-loop" state [4], and conversely facilitating the return to "into-the-loop" or "on-the-loop" state ([5], [6]), the present study focused on the impact of autonomous driving periods of various durations on drivers take-over performance. Indeed, duration has rarely been considered as the main independent variable so far. Thus, it is not clear whether there is a linear relation between duration and driver's state and/or take-over performance. In order to describe more accurately the effect of a long autonomous phase and investigate its possible deleterious effects on regaining control of the vehicle ([1],[2],[3]), we designed a 4 independent groups experiment, each group being associated to a specific duration of the autonomous driving period (5, 15, 45, or 60 minutes). We hypothesized that take-over performance would be more affected in participants experiencing longer durations compared to shorter durations of autonomous driving. The impact of each duration was investigated under two traffic conditions (low traffic: ~7 vehicles/km; high traffic: ~20 vehicles/km), with the same event to manage at the time of TOR signal for the two conditions.

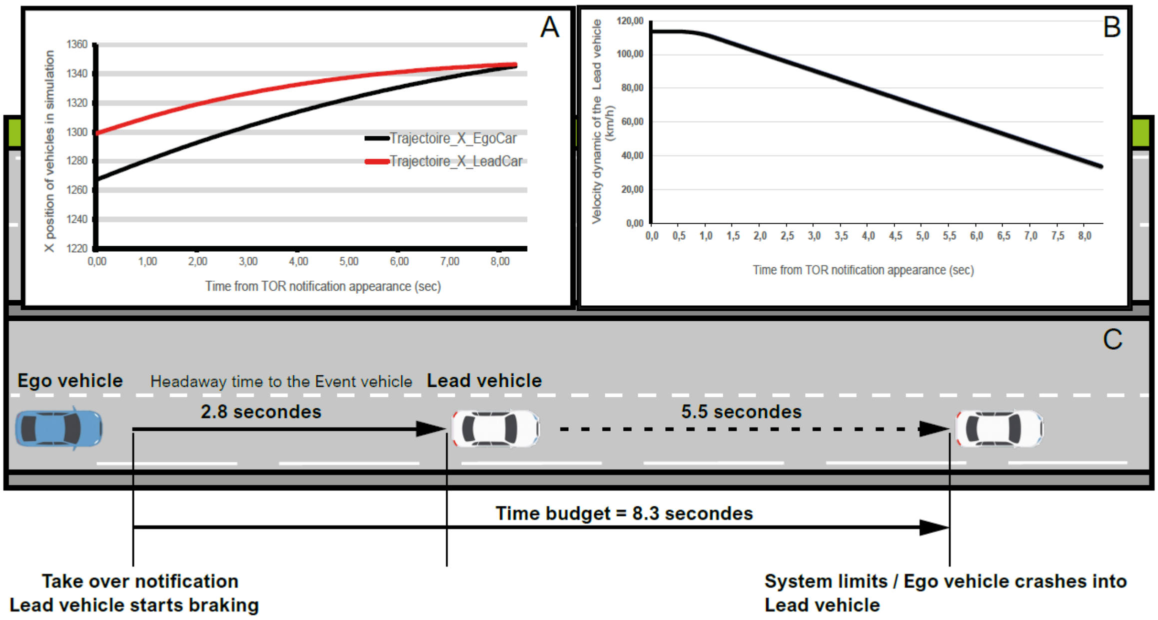

Figure 1. *Illustration of the dynamic of the event to manage at the TOR notification appearance. Top left graph illustrates the dynamic of the position of the lead car (red line) and the ego car (black line) from TOR notification appearance until crash. Top right graph illustrates the deceleration dynamic of the lead car from TOR notification signal. Bottom illustration represents dynamics of the event at time of Take Over Request.*

Fifty drivers (36 males, 14 females) aged between 19 and 35 years old drove a static driving simulator at the Mediterranean Center of Virtual Reality facility. Each group was homogenized by gender balance and driving experience (at least 18 months of driving, ~ 8 000 km/year). Participants were equipped with physiological and oculomotor (Tobii) sensors, in order to assess afterward the drowsiness status ([7]) and gaze behavior around TOR time. After that, they ran a habituation session lasting 13 min to familiarize themselves with the simulator, the take-over request (TOR) signal and the way to activate and deactivate the “Highway Chauffeur” function. Then, they ran two driving sessions (one per traffic condition, “Low” and “High” in a randomized counterbalanced order) conducted on a highway loop at 113.5 km/h with an automatic gearbox. One session proceeded as follows: participants drove under manual mode for 2 minutes at the end of which the system sent a manual-to-autonomous request to activate the “Highway chauffeur” function. After a duration corresponding to the group with which they were associated (5 (N=13), 15 (N=13), 45 (N=13) or 60 (N=12) minutes), a TOR signal was displayed (text and tone). As soon as the TOR signal appears, the car in front (car ahead is present all the session with a headway time of 2.8 seconds; see Figure 1) started to decelerate and conducted to a crash after 8.3 seconds if the participant did not resume control of his vehicle. Participants’ task consisted in resuming manual control of the car by action on brake or acceleration pedal, then performing an avoiding maneuver of the car ahead, getting back into the right lane and continuing for 1 minute of manual driving. During autonomous driving phase of each session, participants were requested to engage into a secondary task (watching a movie on a screen on the right side of the dashboard).
To assess the effect of traffic density and duration of the autonomous phase on driver’s take-over behavior, we analyzed three temporal variables: (1) time from TOR signal to the first glance back to the road; (2) time from the first glance to the first action on a pedal (brake or accelerator) corresponding to the deactivation of the autonomous function (3) the takeover time which is the time from TOR signal to the first action on a pedal. Moreover, we analyzed car trajectories during the avoiding maneuvers and oculomotor strategies before the TOR was displayed. For reasons of brevity, we only present the average takeover times, the standard

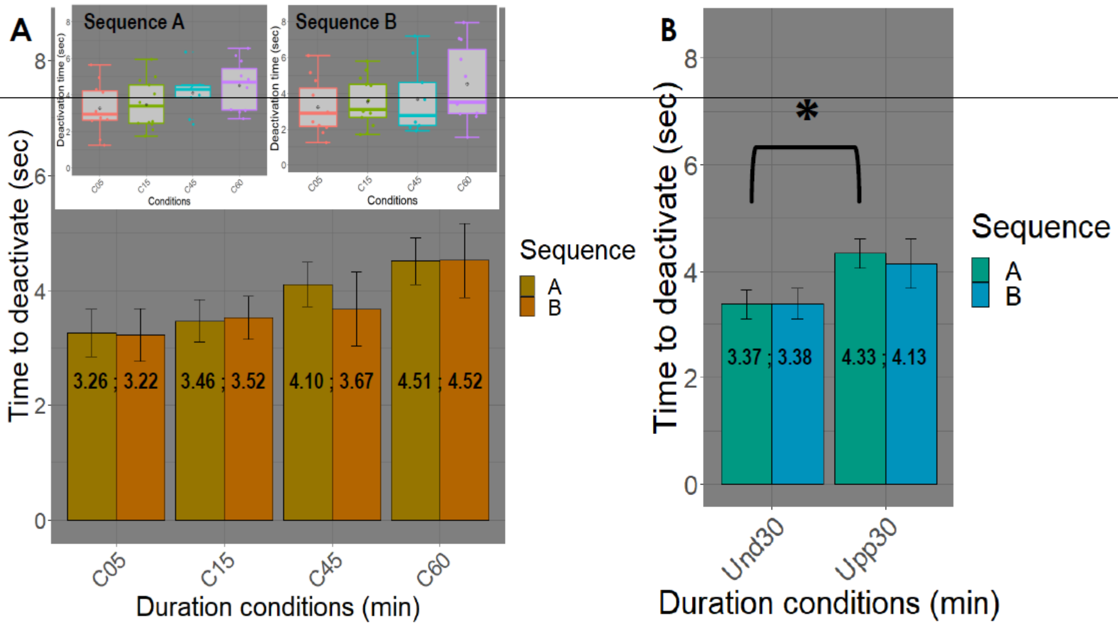

Figure 2. *Panel A: Top panel boxplots illustrate reaction time distribution for each group in each sequence with the mean for each group (black dot). Colored horizontal bars at the ends represent standard deviation, central-colored horizontal lines represent median for each group. Bottom panel: barplots illustrate mean reaction time for each groups and sequences (dark yellow barplot for sequence A; dark orange barplot for sequence B). Horizontal black lines illustrate standard errors. Panel B: Barplots illustrate mean reaction times for short duration groups grouping (Und30) and long duration groups (Upp30). Horizontal black lines illustrate standard errors ;* : p< 0.05.*

deviation between groups and sequence and, the effect of the duration of the autonomous driving phase on driver's take-over behavior (see Figure 2).

We conducted a one-way ANOVA on takeover times between groups for each sequence which did not reveal significant difference between duration (sequence A ($F_{(3,40)} = 2.167$, $p = 0.107$) and sequence B ($F_{(3,40)} = 1.13$, $p = 0.348$) ; Figure 2. Bottom panel). Nevertheless, a linear trend is observed with a longer takeover time increasing as well as autonomous duration in both sequences (around 1s longer for the group C60 compared to the other groups). This trend is confirmed by comparison of grouping the data of short duration groups (Und30 = C05 and C15) and long duration groups (Upp30 = C45 and C60) with a significant difference for the sequence A (mRTUnd30 = 3.37sec (sd = 1.31) ; mRTUpp30 = 4.33sec (1.24) ; $F_{(1,42)} = 6.06$; $p = 0.0179$). This effect disappears in sequence B likely due to a larger standard deviation in the two groups (mRTUnd30 = 3.38sec (sd = 1.41); mRTUpp30 = 4.13sec (2.05) ; $F_{(1,42)} = 2.07$, ; $p = 0.157$) suggesting a potential effect of the sequence's repetition in our procedure ([8],[9]) .

Consequently, takeover times measurement did not allow us to confirm our initial hypothesis that take over performance is strongly influenced by long autonomous duration. However, this result should be interpreted in regard of the individual distribution, sample size and the number of crashes we reported in the experiment. Indeed, we reported interindividual differences within groups illustrated by similar standard deviations in all groups, with short reaction times and long reaction times regardless the autonomous duration (Figure 2. Top panel), likely due to different reaction time profile in our population.
More, unsuccessful trials were removed from the analysis reducing the sample size for each group (we report 4 crashes in group C05 (two in sequence A, N= 11), 7 crashes in group C45 (three in sequence A, N = 10 and 9), and 2 crashes in group C60 (one in sequence A, N=11) and none of the participants in any groups crashed twice. Thus, the linear trend we reported as takeover times increase with autonomous duration did not follow the same dynamic than the occurrence of crashes in groups (C45 > C05 > C60, none for the group C15), reinforcing that critical take over performance is not specifically modulated by the duration.

Furthermore, it remains unclear in our study if the out-of-loop state, which is underlined by longer reaction times or failures, is strictly induced by (i) drowsiness which may have increased due to longer duration of autonomous phases, (ii) attentional tunneling induced by the secondary task, or both. Thus, we will discuss our results in the light of these two impaired states, and the type of non-driving related task we used in our procedure [10].

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References:

[1] Larue, Grégoire S., Andry Rakotonirainy, and Anthony N. Pettitt. "Driving performance impairments due to hypovigilance on monotonous roads." *Accident Analysis & Prevention* 43.6 (2011): 2037-2046.

[2] Bourrelly, Aurore, et al. "Long automated driving phase affects take-over performance." *IET Intelligent Transport Systems* 13.8 (2019): 1249-1255.

[3] Feldhütter, Anna, et al. "How the duration of automated driving influences take-over performance and gaze behavior." *Advances in ergonomic design of systems, products and processes*. Springer, Berlin, Heidelberg, 2017. 309-318.

[4] Louw, Tyron, Natasha Merat, and Hamish Jamson. "Engaging with highly automated driving: to be or not to be in the loop?." (2015).

[5] Louw, Tyron, et al. "Coming back into the loop: Drivers’ perceptual-motor performance in critical events after automated driving." *Accident Analysis & Prevention* 108 (2017): 9-18.

[6] Merat, Natasha, et al. "The “out-of-the-loop” concept in automated driving: Proposed definition, measures and implications." Cognition, Technology & Work 21.1 (2019): 87-98.

[7] de Naurois, Charlotte Jacobé, et al. "Detection and prediction of driver drowsiness using artificial neural network models." *Accident Analysis & Prevention* 126 (2019): 95-104.

[8] Hergeth, Sebastian, Lutz Lorenz, and Josef F. Krems. "Prior familiarization with takeover requests affects drivers’ takeover performance and automation trust." *Human factors* 59.3 (2017): 457-470.

[9] Roche, Fabienne, Anna Somieski, and Stefan Brandenburg. "Behavioral changes to repeated takeovers in highly automated driving: effects of the takeover-request design and the nondriving-related task modality." *Human factors* 61.5 (2019): 839-849.

[10] Mok, Brian, et al. "Tunneled in: Drivers with active secondary tasks need more time to transition from automation." *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems*. 201.

The influence of take-over timings on the driver response process in a lead-vehicle cut-out scenario

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Keywords: Automated Driving; Response process; Take-over Request; Test-track; Wizard-of-Oz

ABSTRACT

Introduction: Previous research, aiming at understanding the effect of automation exposure on driver behaviour in different conflict situations, has found automation to result in unsafe response (e.g., crashing, delayed response) [1, 2]. For example, Victor et al. [2] found that a third of drivers crashed with a conflict object (CO), revealed in a lead-vehicle (LV) cut-out scenario, after having supervised a near-perfect automated system for 30 minutes. In order to design safe vehicle automation, there is a need to understand how to prevent such unsafe responses. For example, would another type of automation, that can trigger a take-over request (TOR) prior to the LV cut-out, be able to prevent drivers from crashing in the conflict as observed in [2]? Further, how far in advance from the CO such a TOR is presented may also influence the safety of the response. The reason is that previous research indicates that a longer take-over-time budget (i.e., the time-to-collision at the TOR) generally results in a longer take-over time (i.e., the time needed for drivers to deactivate automation in response to a TOR) [1, 3]. Consequently, a TOR that is presented early will not necessarily give the drivers more time to respond to a conflict, since these drivers may take longer to deactivate automation. Whereas previous research has focused on how different factors (e.g., the take-over time budget) influence the take-over time, the influence of the same factors on other parts of the response process (e.g., reaction times for hands on the steering wheel, eyes to the HMI) has not received much attention [1, 3].

Aim: This study aimed to examine the driver response process in a LV cut-out scenario after driving with: (a) adaptive cruise control (ACC) and (b) unsupervised automation with a TOR issued 9 seconds or 18 seconds prior to the CO used in the scenario.

Methods: The present study used data from a Wizard-of-Oz experiment on test-track. 48 participants operated a test vehicle (TV) which followed a lead vehicle (LV) on a rural road test-track. The automation feature was implemented using the Wizard-of-Oz approach that simulated the system operation. Each participant drove for a total of 30

minutes with either: (a) ACC or (b) *unsupervised* automation (i.e., an automated system that allows the driver to disengage from the driving task during automation but needs to be prepared to resume manual driving when requested). The participants that drovewith unsupervised automation were free to engage in any secondary tasks of their choice. At the end of the 30-minute drive, all participants experienced a LV cut-out scenario: the LV changed lane to reveal a static “balloon” car in the lane, which required the participants to intervene to avoid a crash. The participants in the ACC-condition received no notification prior to the *conflict appearance* (i.e., the LV changed lane and the static vehicle became visible). For the participants with unsupervised automation, a TOR was triggered at 9 (TOR9-condition) or 18 (TOR18-condition) seconds time-to-collision away from the static “balloon” vehicle (corresponding to 6 and 15 seconds prior to the conflict appearance, respectively). The TOR was a combination of visual (message in DIM) and audio (tone and voice) information. To avoid a collision, the participants pressed two buttons on the steering wheel for approximately 0.6 seconds to deactivate automation, and then performed a steering intervention to pass the CO. Using recorded video and vehicle data, the driver response process was assessed through a *take-over process* for the TOR9- and TOR18-condition, anchored at the TOR, and the *driver steering intervention start*, for all three conditions, anchored at the time point when the drivers passed the CO (i.e., when the longitudinal distance between the TV front and CO was zero). The take-over process consisted of timings, after the TOR, for: (a) first glance to HMI, (b) first glance forward, (c) hands on the steering wheel, (d) automation deactivated, (e) end of secondary task engagement, (f) start of second button press (if the first one did not succeed to deactivate automation), (g) eyes on path from now on, (h) first brake, and (i) start of steering intervention (to pass the CO). In addition, glance locations at the TOR presentation (i.e., on task (TASK), forward (FWD) or other (OTHER)), and timings for the LV cut out and passing of the CO were also coded.

Results & Discussion:
The results show that the first part of the take-over process was independent of the TOR timing. The majority of the participants had showed a first glance towards HMI, a first glance to the forward road, ended their secondary task (if a task was present), put hands on the steering wheel and deactivated automation within about 6 seconds from the TOR (see Figure 1a). However, three participants within the TOR18-condition, needed longer time to deactivate automation. Two of these participants (Participant ID 36 and 43 in Figure 1a) did not manage to deactivate automation at their first attempt, since they either pressed the buttons too short time (i.e., shorter than 0.6 s) or they pressed next to the button instead of on it. The third participant with long take-over time, was engaged in two secondary tasks (mobile phone and notebook) and sat in a relaxed position (with both feet up on the car seat) at the time of the TOR. Further, the results indicate that the LV cut-out triggered the start of steering intervention independent of TOR timing: in Figure 1a, all the brown plus-signs occur to the right of the vertical line which marks the LV cut-out. Finally, the most clear difference between the two TOR timings seem to be that: (a) the earlier the TOR, the longer it takes until the drivers direct and keep their eyes on the road/threat (i.e., *eyes on path from now on* generally occur later for the TOR18- compared to TOR9-condition) and

(b) the first driver braking, generally, takes place prior to the conflict appearance in TOR18, and after the conflict appearance in TOR9.

Surprisingly, the present study could not confirm the previously found delay in conflict response for automated driving [1, 2]. Rather, Figure 1b indicates that the safest response

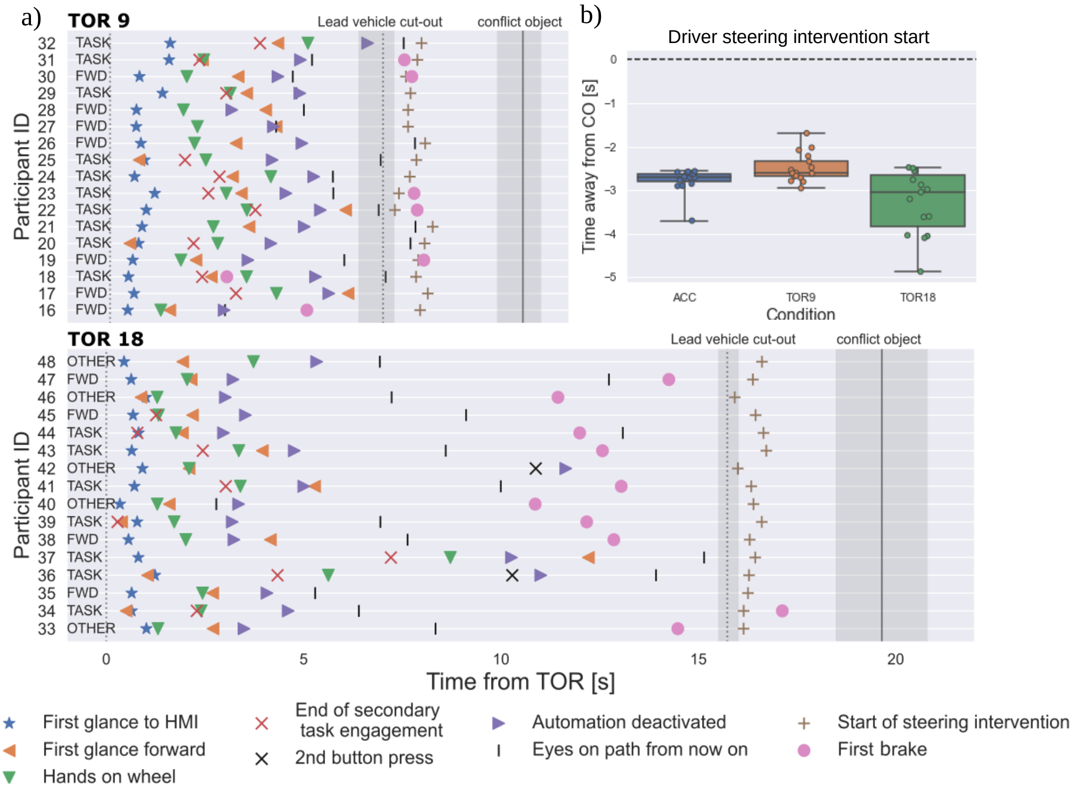

Figure 1a): *Take-over process for TOR9- (top panel) and TOR18- condition (bottom panel). Text marks the glance position at the TOR and markers represent different driver actions performed sometime between the TOR and passing of the CO. Vertical lines mark the TOR, the LV cut-out (shaded band displays the range) and the CO (shaded band displays the range).* ***b):*** *The start of the steering intervention (anchored at the CO) for ACC-, TOR9- and TOR18-conditions.*

(earliest driver steering intervention start) was achieved by the participants in the TOR18-condition, followed by the ACC-condition, and then the TOR9-condition. A one-way Kruskal Wallis test (α = 0.05) indicated a significant effect of the steering intervention times across the three conditions (H = 12.0, p = 0.002). Post-hoc comparisons using Dunn's test further indicated that the steering intervention time for TOR9 (Mdn = –2.61 s, SD = 0.33 s) happen statistically significantly later than for TOR18 (Mdn = –3.01 s, SD = 0.71 s; p = 0.0005). The steering intervention times for ACC (Mdn = –2.69 s, SD = 0.28 s) did not statistically significantly differ from the other two conditions. Note that, in the present study, ACC served as baseline condition for manual steering, since a fixed time headway between the TV and the LV was needed in order to achieve the same conflict criticality across conditions. Triggering the TOR early seems to result in that the participants can notice the conflict object early (e.g., before the conflict appearance) and adopt a precautionary behavior (e.g., brake). Consequently, these drivers will be farther away from the CO at the conflict appearance and can therefore start their steering intervention earlier compared to the drivers that are presented with the TOR later and do not slow down before the conflict appearance. In fact, obtaining the TOR later may even prevent the drivers from noticing the conflict since the take-over procedure may require drivers to look off path (e.g., look at HMI to obtain feedback about automation deactivation etc.). This could potentially explain the slight delay in response for TOR9-participants compared to the ACC-participants.

Finally, presenting a TOR prior to the conflict appearance, did not result in drivers that respond too late. In contrast to Victor et al. [2], none of the drivers in the present study crashed with the CO. Importantly, Victor et al. [2] concluded that the drivers crashed because they did not understand the need to act, because they expected the automated vehicle to act and resolve the conflict. Thus, it seems that when automation trigger a TOR prior to the conflict appearance, drivers understand their responsibility of having to act. In fact, the present study shows that an early TOR provide the drivers with more time to monitor and understand the situation, and they may even adopt a precautionary behavior (i.e., slowing down); giving them more time to respond to the conflict.

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References:

[1] McDonald, A., et al.: 'Toward computational simulations of behavior during automated driving takeovers: a review of the empirical and modeling literatures', Human factors., 2019, 61, (4), pp. 642-688.

[2] Victor, T. W., Tivesten, E., Gustavsson, P., Johansson, J., Sangberg, F., & Ljung Aust, M.: 'Automation expectation mismatch: Incorrect prediction despite eyes on threat and hands on wheel', Human factors, 2018, 60, (8), pp. 1095-1116.

[3] Zhang, Bo, et al. 'Determinants of take-over time from automated driving: A meta-analysis of 129 studies.', Transportation research part F: traffic psychology and behaviour., 2019, 64, pp. 285-307.

Driver monitoring during automation: disentanglement of activities and emotions

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Keywords: Automation, emotion, auditory distraction, neuroergonomics, physiology, driver monitoring.

ABSTRACT

Advances in technological and industrial research in the automotive sector suggest the imminent introduction of Level 3 automated personal vehicles (an automated car requiring sporadic supervision by the driver, who must be able to regain control of the vehicle if necessary), Level 4 (no-human interaction required under certain conditions) or 5 (fully driverless automated vehicle) (SAE automation levels). Traffic policies are evolving to allow the deployment of autonomous vehicles. These technological advances raise questions in terms of road safety. Notably, these questions concern human-machine interaction and the allocation of driver's attention during the use of automated systems. Future vehicles should give the opportunity for the driver to do something else than driving. Therefore, it will become necessary to supervise drivers in their activities to keep them in the loop when needed.

Vehicles currently on the market are equipped with Level 1 or 2 automation systems. Research on automation has shown that the use of systems such as Advanced Driver Assistance Systems (ADAS) can lead to over-reliance, over-dependence or misuse, even if the system is not completely effective [1]. According to [2], "excessive trust can lead to rely uncritically on automation without recognizing its limitations or fail to monitor the automation's behavior". However Level 3-4 automated vehicle prototypes are being developed rapidly. In these levels, taking back the control of vehicles is still needed to ensure safety of driver and other road users. Relying on the system can lead to a passive fatigue in the sense that the driver should have too few things to do while driving [3; 4], leading to an under activation. This could hamper the mobilization of attentional resources when needed to respond to take-over requests [5]. Any of these two effects could be detrimental on the different steps needed while taking the driver back in the loop. A minimum state of vigilance is required to monitor the system optimally [6]. Inattention episodes are already observed when driving non-automated vehicles, although drivers' attentional resources are supposed to be entirely dedicated on the driving task. Indeed, an epidemiological study has shown that, among a population of drivers admitted to an emergency department following a car crash, the

probability to be considered responsible of the crash increased when the driver reported to mind wander just before the crash [7]. The proportion of accidents linked to inattention to driving being not negligible, it is necessary to address these road safety issues by notably taking into account driver's state during the use of automated vehicle.

The objective of the research presented in this paper is twofold: 1) identify the drivers' activity (either processing external stimuli to the driving context, e.g. when listening a broadcast or not) using physiological data; 2) disentangle the drivers' emotional state (neutral vs. sadness) using physiological indicators.

To do so, 20 participants were involved in this research (11 males, mean age=27.15, SD=4.65). All participants had their driving license for at least 3 years (M=7.5, SD=3.69). Participants were asked to drive on a highway and on a country road. After two minutes of manual driving, they were asked to switch to an automated driving mode. During this mode, participants had four different tasks: 1) listening to an audio broadcasting neutral content (stories about nature or science), 2) listening to stories with sad content, 3) performing an imagination task (imagine a story based on two cards representing a personage and a place) and 4) driving after written the saddest experience they ever lived (autobiographical recall). The purpose of the imagination task was to produce some non-driving related thoughts. The recall task was designed to make the participants mind-wandering with a general sad emotional state. The four conditions were counterbalanced into four different driving scenarios. After 8 minutes of automated drive mode, an unplanned take-over was requested (TOR). Participants had then to take back the manual control of the vehicle in accordance with the safety rules. To sum-up, we manipulated the Activity the participants had to perform during the automated mode (listening vs. non-listening) and the Emotion (neutral vs. sadness). Different physiological data were recorded in order to assess the participant internal state: heart and respiratory activities. Reaction times to the TOR were also collected from the steering wheel or the pedals.

We assessed the emotional state with an adapted version of the Geneva Emotional Wheel [8]. As expected, participants reported to be more sad in the listening of sad stories than when listening to neutral stories ($p<.001$). They also reported to be more sad when asked to recall their personal experience than when asked to imagine a story ($p<.001$). No statistical differences were observed when comparing the two sad conditions (listening to sad stories and autobiographical recall). Both conditions (listening or not) seem to induce comparable emotional states. Similarly, no differences were observed when comparing the two neutral conditions.

The physiological results showed a main effect of Emotion on the heart rate variability assessed using the standard deviation of normal to normal heartbeat intervals (SDNN) ($p<.001$). For the respiratory period, a main effect of the Activity (listening > non-listening, $p<.01$) was observed. Post-hoc analysis revealed a statistical difference between listening and non-listening in the neutral condition ($p<.05$). The analyses performed on the respiratory amplitude revealed also a main effect of the Activity (listening < non-listening, $p<.01$) but also a difference in the sadness condition (listening > non-listening, $p<.01$). Finally, the ANOVA conducted on the reaction times revealed that participants responded slower to the TOR in the non-listening task only under neutral condition ($p<.05$).

These results reveal the possibility to use different physiology-based features to disentangle both drivers' activity (listening or not) and emotional state (sad or neutral). Actually, the heart rate variability could be interesting to use in order to disentangle the drivers' emotion (sadness). The respiratory amplitude could complement this information to define the driver's activity that is the activity linked to the sad emotional state (listening task or the recall of a sad event). Moreover, the use of the respiratory period could be helpful, as suggested in [9] to distinguish the driver's activity (listening or not) in the neutral conditions. Finally, the participants were slower to take back the control when they were thinking to other things than driving. All these results put together show the importance to take into account different features to disentangle the drivers' activity and emotion. Even if our results only show an effect of mind-wandering on the reaction time to take back the manual control, other effects could happen. For instance, detrimental effects of negative emotions have been shown on the perception of an alert by pilots (see [10]). Additional works are still needed to address this issue further with regard to other activities and mental states and to integrate these physiology-based features in monitoring diagnostics.

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References:

[1] D. de Waard, M. van der Hulst, M. Hoedemaeker, and K. A. Brookhuis, 'Driver Behavior in an Emergency Situation in the Automated Highway System', *Transp Hum Factors*, 1999, 1(1): 67–82.

[2] R. Parasuraman and V. Riley, 'Humans and automation: Use, misuse, disus, abuse', *Hum Factors, 1997,* 39, (2):230–253.

[3] J. F. May and C. L. Baldwin, 'Driver fatigue: The importance of identifying causal factors of fatigue when considering detection and countermeasure technologies', *Transp Res Part F Traffic Psychol Behav*, 2009, 12(3):218–224.

[4] D. J. Saxby, G. Matthews, J. S. Warm, E. M. Hitchcock, and C. Neubauer, 'Active and passive fatigue in simulated driving: Discriminating styles of workload regulation and their safety impacts.', *J Exp Psychol: Appl* 2013, 19, (4): 287–300.

[5] M. S. Young and N. A. Stanton, 'Attention and automation: New perspectives on mental underload and performance', *Theor. Issues Ergon. Sci.*, 2002, 3(2): 178–194.

[6] R. Parasuraman, 'Human-Computer Monitoring', *Hum Factors*, 1987, 29(6): 695–706.

[7] C. Galera et al., 'Mind wandering and driving: responsability case-control study', *Brit Med J*, 2012, 345:1–7.

[8] K. R. Scherer, V. Shuman, J. R. J. Fontaine, and C. Soriano, 'The GRID meets the Wheel: Assessing emotional feeling via self-report', in *Components of Emotional Meaning: A sourcebook*, J. R. J. Fontaine, K. R. Scherer, and C. Soriano, Eds. Oxford: Oxford University Press, 2013, pp. 281–298.

[9] A.R. Hidalgo-Muñoz et al. 'Respiration and Heart Rate Modulation Due to Competing Cognitive Tasks While Driving' *Front Hum Neurosci*, 2019, 12:525.

[10] F. Dehais et al. 'Failure to detect critical auditory alerts in the cockpit: evidence for inattentional deafness', *Hum Factors*, 2014, 56(4):631-644.

4

Approach used to merge the different driver monitoring diagnostics in the AutoConduct project

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Keywords: Automation, driver-monitoring fusion, posture, visual strategy, attention

ABSTRACT

Driving automation, either level 3 (including unplanned manual control recovery) or level 4 (fully automated driving on specific road sections), introduces new safety and acceptance issues. In order to improve road safety by integrating advanced safety technologies, we must ensure that this new technology takes into account the needs and expectations of the drivers, on the one hand, and the predicable changes in user behaviour, on the other hand. A Human Factors working group, bringing together the main French actors of driving automation, has been set up within the NFI plan (investment plan for the future) "autonomous driving" to prioritize these issues (www.economie.gouv.fr/files/files/PDF/nouvelle-france-industrielle-sept2014.pdf).

Project presentation

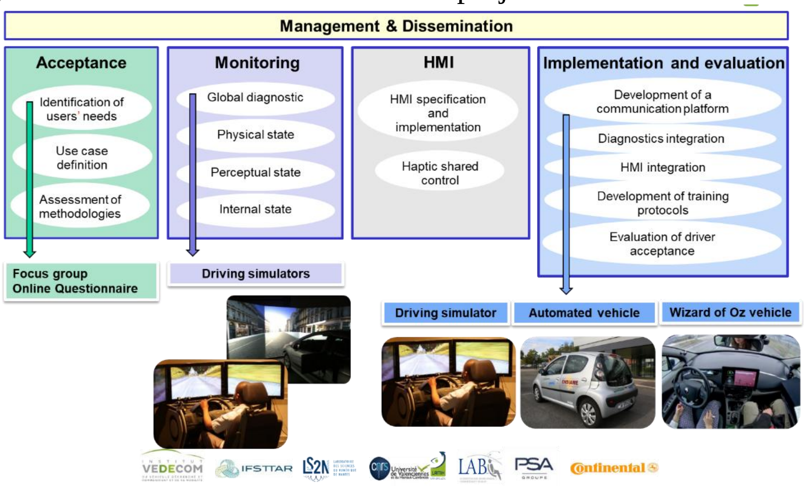
AutoConduct aims to design a new Human-Machine Interaction (HMI) based on needs analyses and adapted to the driver's condition in response to the priorities identified by this working group. For this purpose, the current project offers advanced monitoring of the driver by combining different diagnoses (physical state defined by the posture, internal states defined by emotions and cognitive load, and perceptive state defined by visual strategies) to adapt the management of interactions between the driver and the vehicle automation in real time. The originality of this project is

- To adopt a user-centric approach based on the needs of human factors and ergonomics;
- Consider acceptance (a priori and after experience with the system) at the early, design stages of automated vehicle, which, until now, were developed primarily based on technological criterion;
- To treat the driver's state through objective measures of indicators on three

dimensions: physical, perceptual, and internal (attentional and emotional);
- To develop a progressively shared vehicle control (i.e. cooperation) based on a physiologically valid sensorimotor control model.

The project has been divided into several phases (Figure 1). The first one consisted in a study on acceptance to gain knowledge about the potential needs of the users in realistic cases of autonomous driving and recovery from surveys and interviews. The aim was also to specify possible HMC (Human Machine Cooperation) scenarios used in the subsequent stages of the project The second phase consisted in the design of different technological blocks to monitor the state of the driver characterized by physical, perceptual and internal dimensions. For that, studies have been designed to get new knowledge on the measurements characterizing the driver states and to develop tools and methods to obtain indicators on these states in real time on the three physical, perceptive and internal dimensions. The third phase 'HMI - Interaction Management' aims at designing a progressive shared control system between human and vehicle and an acceptable HMC manager adapted to the driver state. The work of the two previous phases has been integrated on a single simulator in order to provide a diagnostic of the driver states in realistic use cases. Finally, a phase of 'Implementation and evaluation' will then be able to evaluate the integration of these developments done in the partner vehicles.

Figure 1. Organisation of the AUTOCONDUCT project

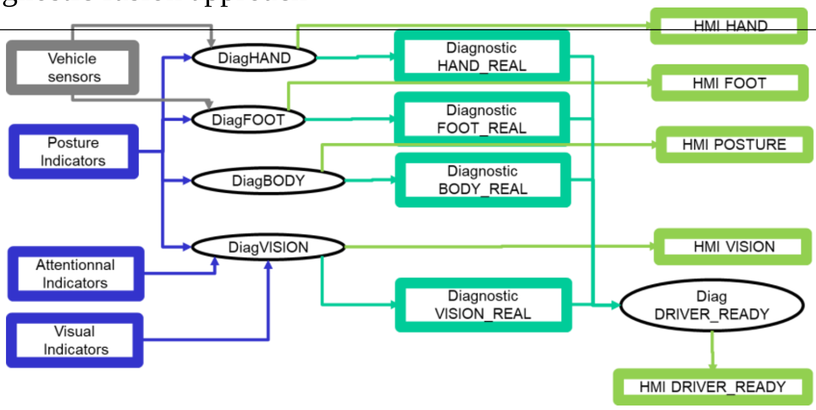


The advanced driver monitoring system and the interface developed by the project has been integrated in two instrumented vehicles. A Wizard of Oz instrumented vehicle (i.e. the active controls are managed by a professional driver hidden from the driver's view) integrates driver monitoring to test robustness of diagnostics on public roads. A second instrumented vehicle integrate the active controls of the speed and direction of the vehicle, to test the acceptance and robustness of HMI in a controlled environment (i.e. test track).

The diagnostic fusion approach

The monitoring of driver's state is based on 3 different types of indicators (Figure 2). The posture module gives some information on the position of the body, the legs and the hands. The visual strategy module gives some information on the position of eyes and on the dynamic visual behaviour. The attentional diagnostic gives information on the driver's attentional level. In addition, some information is given by the vehicle module in terms of driver's actions like pedal and steering wheel movements.

Figure 2. Diagnostic fusion approach



The fusion of these indicators is done in two steps. The first one makes the fusion of several indicators to provide diagnostics: posture and vehicle information to improve the BODY, HAND and FOOT diagnostics, posture, visual and attentional indicators to improve VISION diagnostic. The second step will use these diagnostics to create the final one: DRIVER_READY. The fusion process creates two type of diagnostics. The real diagnostics provide ternary values (Ok, NoOk and undefined) and the HMI diagnostics provides binary value (Ok, NoOk) needed to manage the Human Machine Interaction. The fusion process is done with rules, which define for every combination of input diagnostic values the output diagnostic value. For example, the table 1 define the rules used to create Driver_Ready diagnostic from Posture, Hand, Foot and Vision real diagnostics.

Table 1. Rules used to create Driver_Ready diagnostic

DRIVER_READY	POSTURE	HAND	FOOT	VISION
NoOK	NoOK	All	All	All
NoOK	OK	NoOK	All	All
NoOK	OK	OK	NoOK	
NoOK	OK	OK	OK	NoOK
OK	OK	OK	OK	OK
ok	OK	OK	OK	Undefined
NoOK	OK	OK	Undefined	NoOK
OK	OK	OK	Undefined	OK
OK	OK	OK	Undefined	Undefined

From a useful point of view, this type of table facilitates exchanges between researchers from different disciplines. Indeed, each line describes a well-defined and concrete situation. From an implementation point of view, this approach makes it possible to define which diagnoses are used in priority. It allows an exhaustive coverage of all the possibilities of combining diagnoses.

In conclusion, this project has shown that it is possible to merge diagnostics of very different natures with an exhaustive coverage of the possibilities and to discuss the merging rules with a multidisciplinary team thanks to an exchange format understandable by ergonomists as well as engineers.

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Impact of the driver's visual engagement and situation awareness on takeover quality

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Keywords: Automated driving; Critical events; Human factors; Non-driving task; Situation awareness

ABSTRACT

In Driving, drivers must develop and maintain a good situation awareness [3, 5]. Situation awareness (SA) involves processing the available visual information (SA level 1: perception), developing an understanding of the situation (SA level 2: comprehension) and anticipating the future states of the environment (SA level 3: projection). However, the updating of SA may be discontinuous. According to Rockwell (1988) [6] drivers tend to not spend more than two seconds without taking information about the environment. When it comes to automated driving, especially when a non-driving task is allowed, Rockwell's 2-second rule does not apply. In level 3 automated vehicles (SAE level), Zeeb et al. (2015) [7] reported that the participants looked at the central console without interruption from 2s to 55 seconds during non-driving activities, which can significantly impair and SA. In addition, many studies highlighted a deterioration of take-over quality when performing a Non-Driving Task (NDT) [1, 2, 4, 8]. In the context of the development of the level 3 automated vehicles, it is essential to understand the extent to which a loss of SA can be detrimental, especially in the event of a critical takeover request.

Objectives

The aim of the study was to evaluate the quality of takeover in a critical obstacle avoidance situation requiring good situational awareness. The relative importance of two periods preceding the takeover was focused:

- A period of 5 minutes preceding the TOR: The hypothesis was that being engaged in a secondary task during this long time prevented the construction of a mental model of the environment allowing the driver to anticipate the consequences of the obstacle's appearance (SA level 3).

- The last two seconds before the TOR: The hypothesis was that being engaged in a secondary task during this short time prevented the perception of the immediate environment just before having to deal with the critical situation (SA level 1 & 2).

Methods

96 subjects participated in this study on a fixed-base driving simulator. The driving environment was displayed on three screens. A smaller screen was dedicated to the dashboard. An 11"-tablet has been added where the center console of a real vehicle would be. It provided information on the state of vehicle automation and allowed to manually switch between manual and automated mode, or the other way around. It was also where the non-driving task was presented. The different screens were divided into several areas of interest to analyze the visual behavior of the participants.

After instructions on operation of level 3 automated vehicle and two 5-minutes training courses, the participants performed one of four automated driving conditions (see Fig. 1):

- Full_SA: the participant was not distracted and was instructed to monitor the road at all times
- SA_NDT: The participant monitored the road at all times, except during the last 2 s before the TOR when he had to read aloud a text scrolling on the tablet (non-driving task, NDT).
- NDT_SA: The participant had to perform the NDT at all time, except during the last 2 s before the TOR when he had to look at the road
- Full_NDT: The participant was distracted during the whole drive up to the TOR.

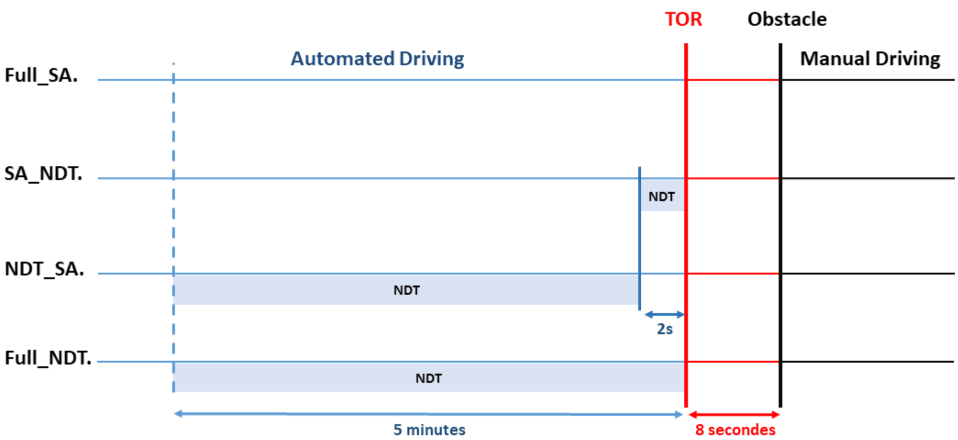

Fig 1. Automated driving conditions

The participant was driving on a 3-lane highway at 110km/h with moderate traffic. At some point, a front vehicle was placed 3 seconds ahead from the participant's vehicle. About 38 seconds before the TOR, the participant's vehicle began to overtake two slower vehicles. The participant's vehicle was then in the centre lane. Right before the TOR, two faster vehicles, separated by 2 seconds, started to overtake the participant's vehicle in order to interfere with the takeover. Then, the front vehicle started an avoidance manoeuvre because an obstacle vehicle blocked the right and centre lanes. At this moment, an auditory

TOR was delivered. The non-driving task was interrupted if there was one, and a red vehicle pictogram indicated the need to take over. To disable the automated mode, the driver could press a button on the tablet or use the pedals or steering wheel. To successfully intervene, the participant had to brake and fit between the two vehicles in the left lane, or to change lane after the second vehicle. Another solution consisted to stop the vehicle in the centre lane before reaching the obstacle. The time headway to the obstacle vehicle at the moment of the TOR was 8 seconds.

After completing the drive, participants were asked to report the vehicles they were aware of at the time of the TOR on a top view image of the situation. The participant's vehicle and the obstacle were already placed at the correct scale and the participants only had to place the other vehicles.

Results

8 trials were rejected due to problems with eye-tracking data and the remaining 88 trials are evenly distributed between conditions. 45 trials resulted in a collision with another vehicle. 23 were with the first fast vehicle, 10 with the second one and 12 with the obstacle. No collisions with vehicles in the right lane occurred.

Data showed an effect of conditions on the occurrence of collisions ($Chi^2 = 8.504$, $p = < .05$). 72,73% of the participants in the Full_NDT condition had an accident, compared to 59.09% for NDT_SA and 36.36% for both Full_SA and SA_NDT. A significant effect of the conditions was found on the awareness of the first fast vehicle before the TOR ($Chi^2 = 32.267$, $p = < .05$): 81.81% of participants were aware of this vehicle for Full_SA and SA_NDT, 45.45% for NDT_SA and 9% for Full_NDT.

Another analysis was performed on the data between the time of the TOR and when the first fast vehicle disappeared in the blind spot of the participant's vehicle (about 2.5 seconds). This period will be referred as "critical phase". It showed a significant effect of the conditions on the number of participants looking at the left mirror and the central mirror ($Chi^2 = 13.149$, $p < 0.05$). When the total time spent on specific areas of interest was considered, there was a significant effect of the conditions on areas not related to driving ($Chi^2 = 14.83$, $p < 0.05$) (see Fig. 2.A) and on the time spent in the left and / or center mirror ($Chi^2 = 17.35$, $p < 0.05$) (see Fig. 2.B). There was no difference for the areas that displayed the driving scene ($Chi^2 = 1.17$, $p = 0.328$). Participants in the conditions Full_SA and NDT_SA spent more time looking at the left / center mirror and less time in the non-driving area compared to Full_NDT and SA_NDT.

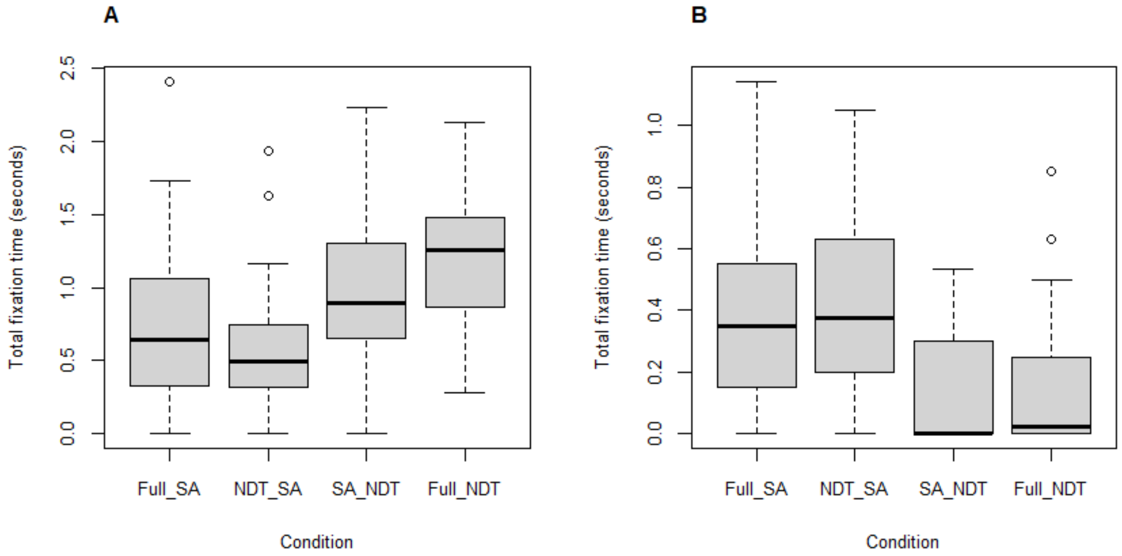

*Fig 2. Total fixation time by condition during the critical phase (**A**: on areas non-related to driving, **B**: on the central and left mirrors)*

Conclusions

The results suggest that monitoring the road at the time of the TOR facilitates adequate visual strategies in the seconds following the TOR. However, this does not appear to be decisive for the success of the takeover. If drivers have not had time to build up situational awareness before the TOR, the risk of accidents was still high even if the vision of the environment was restored 2 seconds before the TOR. Finally, it seemed more important to have good situational awareness at the time of the TOR, even if drivers had just started a non-driving task and only imperfectly checked their mirrors after the TOR. The conclusion is that, in a critical case such as the one used here, helping drivers rebuild situation awareness after the TOR does not appear to be sufficient. It may also be necessary to help the driver maintain a good situation awareness well before the TOR to ensure safety.

References

[1] Eriksson A. S. (2017) Takeover Time in Highly Automated Vehicles: Noncritical Transitions to and From Manual Control. *Human Factors: The Journal of the Human Factors and Ergonomics Society*. 59(4):689-705. doi:10.1177/0018720816685832

[2] Gold C., Damböck D., Lorenz L., Bengler K. (2013) “Take over!” How long does it take to get the driver back into the loop? *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*. 57(1):1938-1942. doi:10.1177/1541931213571433

[3] Kaber, D. B., & Endsley, M. R. (2004). The effects of level of automation and adaptive automation on human performance, situation awareness and workload in a dynamic control task. *Theoretical Issues in Ergonomics Science*, *5*(2), 113‐ 153. https://doi.org/10.1080/1463922021000054335

[4] Merat N., Jamson A. H., Lai F. C. H., Carsten O. (2012) Highly Automated Driving, Secondary Task Performance, and Driver State. *Hum Factors*. 54(5):762-771. doi:10.1177/0018720812442087

[5] Merat, N., Seppelt, B., Louw, T., Engström, J., Lee, J. D., Johansson, E., Green, C. A., Katazaki, S., Monk, C., Itoh, M., McGehee, D., Sunda, T., Unoura, K., Victor, T., Schieben, A., & Keinath, A. (2019). The "Out-of-the-Loop" concept in automated driving : Proposed definition, measures and implications. *Cognition, Technology & Work*, *21*(1), 87‑ 98. https://doi.org/10.1007/s10111-018-0525-8

[6] Rockwell, T. H. (1988). *Spare Visual Capacity in Driving-Revisited : New Empirical Results for an Old Idea*. Vision in Vehicles II. Second International Conference on Vision in VehiclesApplied Vision AssociationErgonomics SocietyAssociation of Optometrists. https://trid.trb.org/view/927089

[7] Zeeb, K., Buchner, A., & Schrauf, M. (2015). What determines the take-over time? An integrated model approach of driver take-over after automated driving. *Accident Analysis & Prevention*, *78*, 212‑ 221. https://doi.org/10.1016/j.aap.2015.02.023

[8] Zeeb K., Buchner A., Schrauf M. (2016) Is take-over time all that matters? The impact of visual-cognitive load on driver take-over quality after conditionally automated driving. *Accident Analysis & Prevention*. 92:230-239. doi:10.1016/j.aap.2016.04.002

The traffic and safety effect of smartphone texting and web surfing during driving in cities: A driving simulator study

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Keywords: driving behaviour, driver distraction, driving simulator, texting while driving, web-surfing while driving

ABSTRACT

Over the last years, in addition to the increasing use of smartphones, new vehicles are equipped with technologies that make it even easier to use a smartphone while driving [1]. For that reason, driver distraction by using a mobile phone is a cause of road traffic accidents [2-3]. International research has indicated that accident probability is increasing when a driver is being distracted [4-5] and especially for the young, distracted drivers this increase is reaching 8% [6]. Moreover, reading text messages while driving reduces the driving speed by 30% [7]. The objective of this study is to quantify the traffic and safety effect of texting and web surfing by a smartphone during driving in urban areas, through a driving simulator experiment.

The experimental procedure was carried out on the NTUA driving simulator which is a motion base quarter-cab manufactured by the FOERST Company. The simulator consists of 3 LCD wide screens 40'', driving position and support motion base. The choice of the sample scheme was focused on young people with a valid driving license. 36 drivers (19 males and 17 females) participated in the experiment, who had 5.4 years of driving experience on average. The sample scheme was clustered into two age groups, aged 18-24 and 25-33, in order to differentiate behavior based on their driving experience. A questionnaire was also developed to identify drivers' profiles and focused on the smartphone use and their familiarity with urban road. At the beginning of the experiment, each participant drove a test route on urban environment during daytime conditions, which was a different route from the scenarios' ones in order to get familiarized with the driving simulator and test for possible simulator sickness issues.

For the present study, the type of road that was examined was urban environment, which included a variety of complex urban conditions: roundabouts, signalized intersections, not-signalized intersections, which required increased cognitive load compared to rural driving environment. Four different scenarios were selected to examine several factors that may have impact on driver's behavior, and the impact of smartphone use while driving. More specifically, the scenarios were distinguished by

day and night driving conditions[1], each with a low (300 vehicles/hour) and high (600 vehicles/hour) traffic volume. In each scenario two unexpected events were programmed to appear in order to examine the accident probability. Drivers were asked by the experiment instructor to perform the following secondary tasks while driving each of the four sessions (day-night and high-low traffic): a) navigate in their Facebook feed, b) texting via Facebook Messenger and c) search for a location via Google Maps app (in random order during their route, but at specific timing given by the instructor).

The statistical analysis that was conducted, included two levels of analysis. The first one included five regression models which were developed in order to analyze the impact of smartphone use (scrolling Facebook feed, texting and Google Maps navigation) while driving on young drivers' behavior and safety in terms of mean driving speed, mean headway distance from the front vehicle and accident probability. The second step included generalized linear models in order to compare the different impacts of the use of different smartphone applications[2]. The elasticity of each independent variable was calculated in order to estimate the sensitivity of each dependent variable [8].

Moving on to the results of the analysis, the mean speed linear regression model indicated that the independent variables which were statistically significant at 95% level were: texting/web surfing distraction, traffic volume, if driver enjoys driving (variable extracted from the questionnaire) and driver's gender. The elasticity value showed that texting or web surfing while driving lead to 8% decrease of the mean driving speed.

The second linear regression model concerned mean speed variability and indicated that the independent variables which were statistically significant at 95% level were: texting/web surfing distraction, traffic volume, how driver changes driving behavior while using mobile phone and driver's daily frequency of texting/web surfing (the latter three variables extracted from the questionnaire). The elasticity value showed that texting or web surfing while driving lead to 26% decrease the mean speed variation. Regarding the mean speed variability, we moved on to the second analysis step with the first generalized linear model, which was also developed, showed (by comparing the significant coefficients) that, Google Maps application had the highest impact in the model, followed by Facebook Messenger and Facebook app. Additionally, the riskiest driver profile was a male driver who is distracted by using the Google Maps app.

Then, the headway distance linear regression model indicated that the independent variables which were statistically significant at 95% level were: texting/web surfing distraction, traffic volume, if driver enjoys driving, how driver changes driving behavior while using mobile phone, driver's daily routes on urban roads, driver's gender and age. The elasticity value showed that texting or web surfing while driving lead to 5% decreased headway distance.

[1] Nightime conditions were fully simulated not only at the driving scenario but also in the environment around the simulator during the experimantal procedure.
[2] The second step conducted only for two out of five examined dependent variables, as for the other three no statistically significant difference was observed between the three different distracted conditions.

Then, a linear mean headway distance variability regression model was developed and showed that the independent variables which were statistically significant at 95% level were: texting/web surfing distraction, traffic volume, lighting conditions (day/night), driver's gender and weekly driven kilometers on urban roads. According to the elasticity values, texting or web surfing while driving lead to 19% decreased headway distance variation. For the mean headway variability, we moved on to the second analysis step with the second generalized linear model, which was also developed, showed (by comparing the significant coefficients) that, Facebook application had the highest impact in the model, then Google Maps and Facebook Messenger app. The riskiest condition was high traffic volume when driver is distracted by using the Facebook app.

Finally, a binary logistic regression model was developed for investigating accident probability, which indicated that the independent variables which were statistically significant at 95% level were: texting/web surfing distraction, traffic volume, driver's age group, lighting conditions (day/night) and driver's weekly days driving on urban roads. The elasticity value showed that texting or web surfing while driving lead to 75% increased accident probability.

Concluding, according to the results of the regression models, a key finding is that web surfing or texting distraction while driving has the greatest negative impact on driving behaviour compared to the other risk factors, such as traffic volume and lighting conditions. More specifically, smartphone use while driving increases significantly the accident probability, while at the same time reduces the mean driving speed. The increased accident probability may be explained by the fact that smaller headways are maintained from the vehicle in front and drivers while using a smartphone have a reduced perception of traffic, which makes them more vulnerable to a driving error and then a collision. Also, using the smartphone while driving reduces the mean speed variability because the distracted driver tries to compensate this risky behaviour by maintaining a steady speed, but this strategy is not successful as the accident risk is greater.

Then, moving on to the results of the generalized linear models, comparing the three different smartphone applications to each other, Google Maps had the highest impact on mean speed variability followed by Facebook Messenger and Facebook application. Combined with the impact of the driver's gender, the riskiest driver profile is a male driver who is distracted by using the Google Maps app. Several remedial measures should be implemented and enforced in order to reduce the use of smartphone while driving as its effect on road safety is detrimental.

References:

[1] WHO & NHTSA, "Mobile phone use: a growing problem of driver distraction", 2011 https://www.who.int/violence_injury_prevention/publications/road_traffic/distracted_driving_en.pdf

[2] Oviedo-Trespalacios O., King M., Haque M. M., Washington S. "Risk factors of mobile phone use while driving in Queensland: Prevalence, attitudes, crash risk perception, and task-management strategies" PLoS ONE, 12(9), 1–16, 2017 https://doi.org/10.1371/journal.pone.0183361

[3] Nasr Esfahani H., Arvin R., Song Z., Sze N. N. “Prevalence of cell phone use while driving and its impact on driving performance, focusing on near-crash risk: A survey study in Tehran” Journal of Transportation Safety and Security, 0(0), 1–21, 2019 https://doi.org/10.1080/19439962.2019.1701166
[4] Choudhary P., Velaga N. R., “Modelling driver distraction effects due to mobile phone use on reaction time”, Transportation Research Part C 77, Indian Institute of Technology Bombay, India, 2017
[5] Drews F. A., Yazdani H., Godfrey C.N., Cooper J. M., Strayer D. L., “Text Messaging During Simulated Driving”, Human Factors Vol. 51, University of Utah, Salt Lake City, 2009
[6] Ortiz C., Ortiz-Peregrina S., Castro J. J., Casares-López M., Salas C. “Driver distraction by smartphone use (WhatsApp) in different age groups” Accident Analysis and Prevention, 117(May), 2018, 239–249. https://doi.org/10.1016/j.aap.2018.04.018
[7] Yannis G., Laiou A., Papantoniou P., Christoforou C. “Impact of texting on young drivers’ behavior and safety on urban and rural roads through a simulation experiment” Journal of Safety Research, 49(February), 2014, 25.e1-31. https://doi.org/10.1016/j.jsr.2014.02.008
[8] Washington S. P., Karlaftis M. G., Mannering F. L., “Methods for transportation data analysis”, CRC Press, Boca Raton, 2011

Processing variable message signs under cognitive distraction

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Keywords: Cognitive distraction, Cognitive effort, Driver information processing, Driving performance, Hands-free phone, Variable Message Signs.

ABSTRACT

Road safety policies in many countries allow the use of a hands-free phone. However, research suggests that this behaviour increases the risk of being involved in accidents, because of the cognitive distraction (for reviews: [1], [2], [3]). Indeed, research also shows that conversing on the phone makes us slower, less stable, and less accurate in some specific visual tasks [4], [5], [6]. There is also some evidence that being involved in a conversation leads to some costs in the processing of verbal information visually presented, in mental arithmetic tasks at least [7].

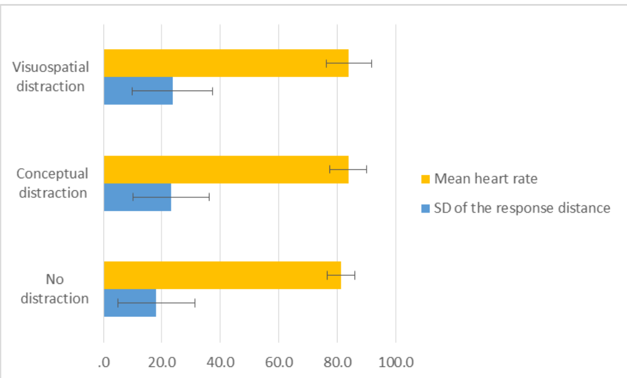
We tested some hypotheses on the effects of cognitive distraction due to a phone call on the processing of text messages provided by variable message signs (VMS) in drivers, and also on their mental effort and vehicle control while processing the VMS, derived from current theories on attention and cognitive control [8], [9], [10]. VMS inform of special circumstances, which can be critical to make driving decisions such as lane changes, route choices, or hazard anticipation. Decisions based on VMS can involve high-level functions such as reading comprehension, memory retrieval, and response selection, and attention can enhance these functions, so a concurrent attention-demanding conversation can compete with the decision-making process. Moreover, verbal processing is involved in both processing VMS and listening to the conversation partner speech, so central attention is also needed to efficiently switch between these two overlapping tasks. Thus, concurrent phone conversation can lead to worse performance in deciding whether the message on a VMS demands immediate actions or not. In addition, mental effort might increase in a driver trying to make such VMS-related decision while talking on the phone, and a rise in heart rate should reflect this effect. Since visuospatial resources are needed to read text messages on VMS, a conversation requiring these resources would be particularly detrimental. However, in quiet traffic conditions, driving tasks such as the control of lateral position or the speed of the vehicle would be supported by processes that are relatively independent from active attention, so the performance of these tasks during the approach to a VMS

should not be substantially altered by distraction from a phone call, neither when the driver's visuospatial resources are relevant nor irrelevant to the conversation.

Eighteen drivers having a Spanish B category driving licence participated. They drove in a driving simulator (Carnetsoft) in a motorway environment, with embedded 3-D models of VMS, posted on straight road sections. Heart electrical activity was continuously recorded (MP100 BIOPAC system). Instructions were given to drive in the right lane at a constant speed, as well as to indicate whether the message displayed on each VMS was a warning message (i.e., informing about potentially dangerous circumstances that would demand an immediate action from the driver, such as 'FLOODED LANE 2KM AHEAD'), or an informative message (i.e., circumstances that would not demand an immediate action, such as 'ACCESS TO TUNNELS 2 KM AHEAD'), as soon as possible while avoiding errors. Responses to this VMS decision task were given manually. All participants completed the task three times. The first one was a no-distraction condition, with no phone calls. In the other two times, the driver was asked to respond phone calls during the route, orally: In the visuospatial distraction condition, the questions engaged the driver's visuospatial cognitive resources, whereas these resources had a relatively minor role in the conceptual distraction condition. An independent experiment indicated that the difficulty question level was similar in the two conditions. We analyzed the effects of this manipulation of cognitive distraction on two aspects of the VMS task performance: a) Response accuracy, as measured by the percentage of correct responses to the VMS task, and b) response distance, i.e., the distance from the driver's vehicle to the VMS when the response to a VMS was given. We also analyzed the effects on the driver's heart rate, their control of the vehicle speed, and their lateral position during approach to VMS. Data were analyzed using the traditional frequentist analysis of variance (ANOVA) and Bayesian ANOVAs.

Response accuracy in the VMS task was lower in the visuospatial distraction condition than in the other conditions. In addition, both the variability of response distance in the VMS task and mean heart rate during the approach to VMS were higher in the conditions with phone calls (Figure 1). In contrast, the variability of vehicle speed and lateral position were similar in the three conditions.

Figure 1. Performance of the VMS task (standard deviation of the response distance to the VMS, in meters) and cognitive effort (mean heart rate) in the distraction conditions.



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These results suggest that the cognitive distraction coming from the use of a hands-free phone affects the processing of messages presented on a VMS, and increase the driver's cognitive effort. The increase of variability of response distance in the VMS task and in mean heart rate under cognitive distraction (either visuospatial or conceptual) indicated that the driver's central attention demands were higher. Moreover, as expected, a diverging pattern of results was observed when considering the specific cognitive resources required by the conversation (i.e., visuospatial or conceptual processing) or the kind of task (i.e., low-demanding driving sub-tasks, such as the lateral or longitudinal control of the vehicle in quiet traffic circumstances, or a higher demanding task, such as making a decision on the VMS contents). Therefore, this study provides new evidence to further discuss previous studies reporting significant or absent effects of cognitive distraction coming from a phone conversation on different aspects of driving. The results also have some implications and provide new evidence to further discuss hands-free phone policies.

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References:

[1] Atchley, P., Tran, A.V., Salehinejad, M.A.: 'Constructing a publically available distracted driving database and research tool', Accid. Anal. Prev., 2017, 99 (Pt A), pp. 306–311.
[2] Strayer, D.L., Fisher, D.L.: 'SPIDER: a framework for understanding driver Distraction', Hum. Factors, 2016, 58, (1), pp. 5-12.
[3] Oviedo-Trespalacios, O., Haque, M., King, M., et al.: 'Understanding the impacts of mobile phone distraction on driving performance: A systematic review'. Transp. Res. Part C Emerg. Technol., 2016, 72, pp. 360-380.
[4] Kunar, M.A., Carter, R., Cohen, M., et al.: 'Telephone conversation impairs sustained visual attention via a central bottleneck', Psychon. Bull. Rev., 2008, 15, (6), pp. 1135–1140.
[5] Gunnell, D.O.A., Kunar, M.A., Watson, D.G.: 'Having a phone conversation delays but does not disrupt cognitive mechanisms', J. Exp. Psychol. Appl., 2020, 26, (2), pp.199-217.
[6] Kunar, M.A., Cole, L., Cox, A., et al.: 'It is not good to talk: conversation has a fixed interference cost on attention regardless of difficulty', Cogn. Res. Princ. Implic., 2018, 3, 33.
[7] Steinborn, M.B., Huestegge, L.: 'Phone conversation while processing information: chronometric analysis of load effects in everyday-media multitasking', Front. Psychol., 2017, 8, pp. 896.
[8] Engström, J., Markkula, G., Victor, T., et al.: 'Effects of cognitive load on driving performance: The cognitive control hypothesis', Hum. Fact., 2017, 59, (5), pp. 734-764.
[9] Navon, D., Gopher, D.: 'On the economy of the human-processing system', Psychol. Rev., 1979, 86, (3), pp. 214-255.
[10] Wickens, C.D.: 'Multiple resources and performance prediction', Theor. Issues Ergon. Sci., 2002, 3, (2), pp. 159–177.

Attitudes towards Distraction and Mitigation Strategies – Implications for School-Based Interventions

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Keywords: Cell Phones, Driver Distraction, Intervention Design, Mitigation, Smartphones, Technology

ABSTRACT

Mobile cellular phones (including smartphones) have become an integral part of our daily activities. College students report using their phones for texting, calling, and other uses in all sorts of seemingly inappropriate situations, such as during class, during meals, while driving, in the shower, at the movies, while studying, and interacting with people face-to-face [1], [2]. When using the phone behind the wheels, studies have found that distraction caused by phone use leads to unsafe behaviors, as reflected by longer reaction times, impaired visual search and lane keeping, and reduced awareness of the driving environment [3], [4]. Given the high prevalence, studies have investigated ways to reduce distracted driving. However, the effectiveness of existing legislative efforts is inconclusive [5], [6]. Government agencies as well as health and safety advocacy organizations are dedicated to combat distracted driving by promoting campaigns and pledges to increase public awareness. The effect of these efforts has been limited and failed to show long-term benefits [7]. Therefore, innovative efforts are critically needed to design beneficial, sustainable, and effective educational campaigns and associated messaging and activities to change behaviors, attitudes, and experiences about distracted driving [8], [9].

The current qualitative study was designed to: 1) Understand college students' attitudes towards technology use and phone use behaviors, social factors related to distracted driving, mitigation strategies, and laws and perceived effectiveness. 2) Collect ideas for interventions for a college-based campaign.

Focus groups with college students were then conducted to gather their experiences, behaviors, perceptions, and attitudes related to technology and phone use while driving (9 focus groups were conducted, number of participants varied between 4 and 8). A focus group guide was developed that included the aforementioned topics related to distracted driving. At the end of each focus group, participants were asked to report their level of engagement in technology and phone use behaviors while driving on a scale of 1 to 5, with 1 being never and 5 being very often, in the past 3 months (own behavior). In addition, participants reported the level of engagement in these activities they believe a safe driver in their age group would do (expected behavior). Each focus group session lasted about 1 hour, and participants were compensated for $30. This study received approval from the Institutional Review Board for conducting human subjects research from the authors' university.

A total of 56 students (32 women, 42 with unrestricted driver's license, 14 with restricted license, 33 Whites) currently enrolled in a university in Northeastern US were recruited. The average age of the participants was 19.93 (SD = 1.49), average age

when obtained their driver's license was 16.73 (SD = 0.98), all but 3 lived in urban or suburban areas, 70% of them drove at least 2-4 times a week, most of them did not have any major and minor accidents in the past 3 years (91% and 59%, respectively), and most of them self-reported always wore a seat belt when they were a driver and a passenger in the past month (86% and 73%, respectively).

Table 1 lists the 6 most frequent (out of 17) self-reported technology and phone use behaviors when the participants were the driver (averaged rating above 2.5) and the corresponding expected behaviors from a safe driver in their age group as well as the results of paired sample t-test. On average, participants' own behaviors were less ideal than those of their expected safe peers.

Activity	Own behavior	Expected behavior	t-test
Chatting with passengers if there are any while driving	4.56	3.44	6.21*
Adjusting the audio system using controls on the console while driving	4.38	3.02	7.40*
Manually entering an address into a navigation app on a smartphone that is not mounted inside the vehicle while the car is moving	3.07	2.02	4.86*
Reading a text message on a hand-held device (e.g., cell phone) while the car is moving	2.71	1.97	3.45*
Talking on a hand-held cell phone while driving	2.71	2.15	2.56*
Talking on the phone using a hands-free device (e.g., Bluetooth headset)	2.57	2.74	-1.13

*Denotes significance at .05 level

Table 1. Secondary task engagement: own vs. expected behaviors from a safe driver.

After transcribing the audio recordings from the focus groups, inductive thematic analysis [10] was used to identify and analyze themes within this qualitative data. A few themes emerged from the focus group: 1) Projected and actual technology use: most participants reported needing, wanting, even being forced to use technology to accomplish daily tasks. Participants expressed feeling lost and disconnected without their phones, for example, "cannot call an Uber" if they needed a ride. 2) Current beliefs about phone use while driving: Most participants stated that technology/phone use was a form a distraction and they sometimes "swerved or not checking their mirrors" because they were looking at the phones. Interestingly, many considered checking on songs or music options not distracting, but checking on text messages distracting. 3) Behaviors changed over time: Some said that they initially did not touch their phones much while driving but when they started to see other drivers' phone use behaviors (e.g., texting at a stoplight) and it seemed fine, they started to do it, too. 4) Knowledge of current regulations: Most of the participants were unaware of the laws, but agreed with the idea of punishing people who undermined road safety. Some participants questioned if the bans applied to all aspects of driving, including stopping at a red light. 5) Motivational strategies for mitigation: Participants shared their own strategies (e.g., silencing the phone, keeping it out of reach) and suggested methods for minimizing problematic phone use, such as increasing fines and tickets, making the phone less appealing, and increasing insurance rates. Most participants wanted to change the norms about having the pressure to respond right away.

Overall, there are misperceptions of safety and acceptable behaviors (e.g., texting is safe and legal at red lights). There is also discrepancy between own behaviors and expected behaviors from a safe driver. Understanding college students' experiences, perspectives, and attitudes about technology/phone use could help design interventions that target adolescents and young adults as they start driving and living independently and being responsible for their own finances and safety. Intervention strategies should capitalize their desires to be socially and technologically current, knowledge about phone use, and wishes for safety and entertainment while driving. For example, one intervention could focus on comparing checking on music vs. text messages while driving in a portable driving simulator.

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References:

[1] M. A. Harrison and A. L. Gilmore, "U txt WHEN? College students' social contexts of text messaging," *Soc. Sci. J.*, vol. 49, no. 4, pp. 513–518, Dec. 2012, doi: 10.1016/j.soscij.2012.05.003.

[2] D. R. Tindell and R. W. Bohlander, "The use and abuse of cell phones and text messaging in the classroom: A Survey of college students," *Coll. Teach.*, vol. 60, no. 1, pp. 1–9, Jan. 2012, doi: 10.1080/87567555.2011.604802.

[3] D. L. Strayer and D. L. Fisher, "SPIDER: A framework for understanding driver distraction," *Hum. Factors*, vol. 58, no. 1, pp. 5–12, Feb. 2016, doi: 10.1177/0018720815619074.

[4] World Health Organization and National Highway Traffic Safety Administration, "Mobile phone use: A growing problem of driver distraction," Geneva : World Health Organization, Geneva, 2011. Accessed: Oct. 24, 2018. [Online]. Available: http://apps.who.int/iris/handle/10665/44494.

[5] Highway Loss Data Institute, "Hand-held cellphone laws and collision claim frequencies," *Highway Loss Data Institute Bulletin*, vol. 26, no. 17, 2009.

[6] A. T. McCartt and L. L. Geary, "Longer term effects of New York State's law on drivers' handheld cell phone use," *Inj. Prev.*, vol. 10, no. 1, pp. 11–15, Feb. 2004, doi: 10.1136/ip.2003.003731.

[7] B. Joseph *et al.*, "Injury prevention programs against distracted driving: Are they effective?," *Traffic Inj. Prev.*, vol. 17, no. 5, pp. 460–464, Jul. 2016, doi: 10.1080/15389588.2015.1116042.

[8] L. S. Arnold *et al.*, "Effectiveness of distracted driving dountermeasures: A review of the literature (research brief)," AAA Foundation for Traffic Safety, Washington, DC, Nov. 2019. Accessed: Nov. 19, 2019. [Online]. Available: https://aaafoundation.org/effectiveness-of-distracted-driving-countermeasures-a-review-of-the-literature/.

[9] W. Li, K. Gkritza, and C. Albrecht, "The culture of distracted driving: Evidence from a public opinion survey in Iowa," *Transp. Res. Part F Traffic Psychol. Behav.*, vol. 26, pp. 337–347, Sep. 2014, doi: 10.1016/j.trf.2014.01.002.

[10] V. Braun and V. Clarke, "Using thematic analysis in psychology," *Qual. Res. Psychol.*, vol. 3, no. 2, pp. 77–101, Jan. 2006, doi: 10.1191/1478088706qp063oa.

Assessing secondary task demand while driving using the Box Task versus the Lane Change Task – A comparison of two methods

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Keywords: Box Task, Lane Change Task, Evaluation methods, In-vehicle information systems

EXTENDED ABSTRACT

In-vehicle information systems allow drivers to engage in secondary tasks, such as selecting music via the infotainment system, while driving. However, interacting with such systems can lead to visual, manual as well as cognitive distraction. Assessing in-vehicle system demand while driving is, therefore, a central topic in driver distraction research. There is evidence based on different studies that visual-manual secondary tasks are associated with a decrease in driving performance, especially due to long off-road glances [1]. Interacting with voice-based in-vehicle systems is, however, also not without controversy [2]. Findings indicate that voice-based commands lead to cognitive distraction, and hence, to longer reaction times and greater speed variability [e.g., 3, 4, 5]. Others, however, reported that cognitive demand while driving is associated with improved driving performance parameters, such as a better lane keeping [e.g., 6].

In order to avoid collisions due to distraction, it is car manufacturers' responsibility to minimize distraction elicited by integrated in-vehicle information systems. To assess this, easy-to-implement and low-cost methods are needed. One of these methods is the Lane Change Task (LCT) developed by Mattes [7]. According to the ISO standard [8], participants' path deviation serves as a measure for secondary task demand in the LCT. However, this measure cannot distinguish accurately between different secondary task demands (e.g., visual, manual or cognitive ones; see e.g., [9]). In this area, the combination of the Box Task and the Detection Response Task (BT+DRT; [10]) is a relatively new method, which is based on the Dimensional Model of Driver Demand [see 11]. During the BT, participants' physical (i.e., visual-manual) demand associated with the driving task in a car-following scenario is assessed. Simultaneously, participants have to react to a tactile stimulus, which makes it possible to assess cognitive demand (see DRT, [12]). Thus, different secondary task demands can be assessed separately. However, to date, there has only been little research on the sensitivity of the BT+DRT (see [13]).

The objective of the present study was to validate the BT+DRT by comparing the sensitivity of this method with the sensitivity of the already established LCT.

Method

Participants: Fifty-two participants (26 female, 26 male) with a mean age of 44 years (SD = 20.19) took part in this study.

Design. A 2 x 5 within-subject-design was used, with method (BT+DRT, LCT) and secondary tasks (no secondary task, visual-manual easy, visual-manual difficult, cognitive easy, cognitive difficult) as independent variables.

Material: In the BT+DRT condition, participants had to hold a blue box within two yellow boundaries (see Figure 1). The box was changing its size and position within a sinusoidal pattern. To adjust box position and box size, steering wheel and gas pedal had to be used, respectively. Simultaneously, participants had to react to a tactile stimulus located on participants' right shoulder by pressing a button on the steering wheel. According to the ISO norm [11], the stimulus consisted of a vibration every three to five seconds. In the LCT condition, participants were instructed to drive on a three-lane road with a constant speed of 60 km/h. Participants had to change lanes according to signs appearing along the roadside. As visual-manual secondary task, the Surrogate Reference Task (SuRT; [14]) was used in an easy and difficult version. To assess cognitive demand, participants had to engage in an easy and difficult counting task (see [15]).

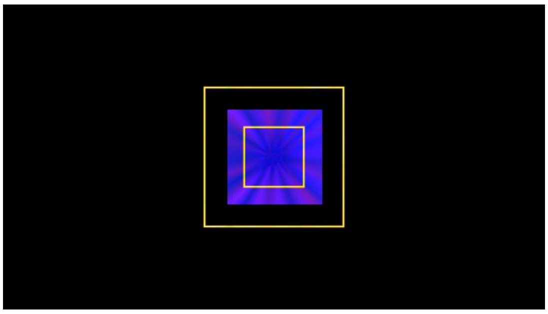

Figure 1. Box Task example screen: The two yellow squares represent the guide boxes (i.e., inner and outer boundaries).

Procedure. Participants had to complete two test blocks (BT+DRT and LCT). After familiarizing themselves with the primary driving task (BT+DRT/ LCT), participants completed a baseline run. Afterwards, the four secondary tasks had to be performed in addition to the BT+DRT/ LCT. Participants should "drive" safely and should engage simultaneously in the SuRT or counting task (i.e., attention should be paid to both the primary driving task and the secondary task). Each run lasted approximately three minutes. Methods and secondary tasks were balanced.

Results

Regarding the BT, the variability of box position (SDLatP) and box size (SDLongP) serve as measures of physical demand. Friedman's ANOVA revealed significant results in terms of box position variability (χ^2 (4) = 99.247, p < .001) and box size variability (χ^2 (4) = 84.727, p < .001) across the secondary task conditions. Participants performance in the BT was the best during the baseline, the worst during the difficult SuRT condition (see Figure 2). Moreover, the results concerning the DRT showed that hit rate was lowest and mean reaction time was highest during the difficult counting condition. Regarding the LCT, we analyzed participants' path deviation (MDEV) using the adaptive model. Similar to the results of the BT, Friedman's ANOVA revealed significant differences across secondary task conditions (χ^2 (4) = 82.338, p < .001). Here too, participants showed the lowest mean deviation during the baseline, the highest during the difficult SuRT condition (see Figure 2).

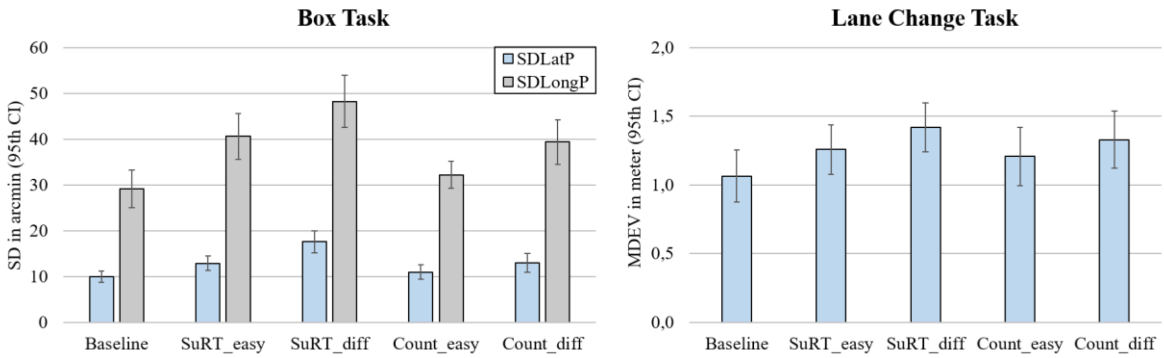

Figure 2. Mean standard deviation of box position and box size in the BT (left) as well as mean deviation in the LCT (right) across the secondary task conditions.

Moreover, secondary task performance and mental workload differed significantly between BT+DRT and LCT, indicating that performing the LCT was more demanding than performing the BT+DRT. This difference was particularly pronounced with regard to the visual-manual secondary task SuRT.

Conclusion

The results of the present study indicate that the BT is a sensitive method to investigate visual-manual secondary task demand while driving. The results were comparable to those of the LCT. However, because of the integration of the DRT, the BT+DRT offers the opportunity to distinguish between different dimensions of driver distraction. Both LCT and BT seem to be especially sensitive to visual-manual distraction effects, while the DRT mainly covers cognitive demand. However, it has to be noted that the BT is also sensitive to cognitive distraction effects, albeit in weakened form. The analysis of mental workload showed that performing the BT+DRT is less demanding than the LCT. Hence, the BT+DRT seems to be a cost-effective and easy-to-implement method to assess in-vehicle system demand.

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References:

[1] Simmons, S. M., Hicks, A., Caird, J. K.: 'Safety critical event risk associated with cell phone tasks as measured in naturalistic driving studies: A systematic review and meta-analysis', Accid. Anal. Prev., 2016, 87, pp. 161-169
[2] Engström, J., Markkula, G., Victor, T., et al.: 'Effects of cognitive load on driving performance: The cognitive control hypothesis', Hum. Fact., 2017, 59, (5), pp. 734-764
[3] Caird, J. K., Simmons, S. M., Wiley, K., et al.: 'Does Talking on a Cell Phone, With a Passenger, or Dialing Affect Driving Performance? An Updated Systematic Review and Meta-Analysis of Experimental Studies', Hum. Fact., 2018, 60, (1), pp. 101–133
[4] Horrey, W. J., Wickens, C. D.: 'The impact of cell phone conversations on driving: A meta-analytic approach (Technical Report AHFD-04-2/GM-04.1)', Illinois: Aviation Human Factors Division, Institute of Aviation, 2004
[5] Rakauskas, M. E., Gugerty, L. J., Ward, N. J.: 'Effects of naturalistic cell phone conversations on driving performance', J. Safety Res., 2004, 35, (4), pp. 453–464
[6] He, J., McCarley, J. S., 'Effects of cognitive distraction on lane-keeping performance: Loss or improvement? ', Proc. Hum. Fact. Ergo. Soc. 55th Annual Meeting, Santa Monica, CA, 2011, pp. 1894–1898
[7] Mattes, S.: 'The Lane-Change-Task as a Tool for Driver Distraction Evaluation', in Strasser, H. et al. (Eds.), 'Quality of work and products in enterprises of the future' (Stuttgart: Ergonomia, 2003), pp. 57–60
[8] ISO 26022: 'Road vehicles - Ergonomic aspects of transport information and control systems - Simulated lane change test to assess in-vehicle secondary task demand', 2010
[9] Engström, J., Markkula, G.: 'Effects of visual and cognitive distraction on lane change test performance', Pro. of the 4th International Driving Symposium on Hum. Fact. in Driver Assessment, Training and Vehicle Design, Washington, 2007.
[10] Hsieh, L., Seaman, S.: 'Evaluation of the Two-Dimensional Secondary Task Demand Assessment Method', Unpublished report, Department of Communication Sciences and Disorders, Wayne State University
[11] Young, R., Seaman, S., Hsieh, L.: 'The dimensional model of driver demand: Visual-manual tasks', SAE Int. J. Transp. Safety, 2016, 4, (1), pp. 33-71
[12] ISO 17488: 'Road vehicles — Transport information and control systems — Detection-response task (DRT) for assessing attentional effects of cognitive load in driving', 2016
[13] Morgenstern, T., Wögerbauer, E. M., Naujoks, F., Krems, J. F., Keinath, A.: 'Measuring driver distraction - Evaluation of the box task method as a tool for assessing in-vehicle system demand', App. Ergo., 2020, 88, 103181.
[14] Mattes, S., Hallén, A.: 'Surrogate distraction measurement techniques: The lane change test', in Regan, M., Lee, J., Young, K. (Eds.): 'Driver Distraction' (CRC Press, 2009), pp. 107–122
[15] Petzoldt, T., Krems, J. F.: 'How does a lower predictability of lane changes affect performance in the Lane Change Task? ', App. Ergo., 2014, 45, (4), pp. 1218–1224

Risk-taking tendencies and not motor inhibition succeed to predict the capacity to drive: a large-scale population study with on-road referencing

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Keywords: Driving performance assessment, inhibition, risk-taking

INTRODUCTION

Executive functions (EF) are a set of cognitive functions that are required to optimize the performance in complex tasks by regulating one's behavior according to internal goals and environmental demands [1]. The study of EF capacities, in particular inhibition, seems to be important to understand the interindividual differences in driving abilities [2,3]. In this context, many studies have focused on inhibition assessed by the interference effect in the Stroop task [3]. However, inhibition is not a unique process and involves attentional and motor aspects that are confounded in the interference effect. Few studies have investigated the implication of the motor counterpart of inhibitory mechanisms in driving abilities [3].

On another note, many studies have found a link between behavioral measures of risk-taking and risky driving in adolescents [4] and offenders [5]. To our knowledge, no study explored the impact of individual differences in performance-based measures of risk-taking on driving behavior. The aim of our study was (1) to analyze separately the predictive power of tasks involving interference resolution and response inhibition and (2) to assess the influence of risk-taking on on-road driving capacities.

MATERIALS AND METHODS

957 participants (457 females), aged from 18 to 92 years old, performed three experimental tasks: the Simon task [6], the Stop Signal task [7] and the Balloon Analog Risk Task [8], followed by an on-road test in 47 testing centers across France.

Simon task Participants performed 2 blocks of 129 trials of the choice reaction time (RT) task in which a stimulus (either a square or a circle) was presented on the right or the left side of a screen. Participants had to respond as fast and accurately as possible according to the stimulus' shape and the stimulus-response mapping: square - right finger press; circle - left finger press. Half of the trials were congruent (the stimulus's location corresponded to the expected response) and half were incongruent (the stimulus's location did not correspond to the expected response). Global RTs and error rates were collected. Interference effect was measured by subtracting the mean RTs on incongruent and congruent trials. Additionally, the Gratton effect was calculated to assess the participants' capacity to engage adequate behavioral adjustments[9].

Stop Signal task Participants performed 2 blocks of 129 trials of the choice RT task in which they had to respond as quickly as possible according to a stimulus (Go signal). In 25% of the cases, a Stop signal was presented during the course of the trial, and indicated to the participants to withhold their response by reactively inhibiting their engaged motor command. The time delay between the Go and the Stop signals was incrementally adjusted according to failed or successful stopped responses in order to compute the Stop Signal Reaction Time (SSRT), an index of motor inhibition capacities. Task design and SSRT calculation were made in agreement with the consensual recommendations of Verbruggen et al. (2019) [10].

Balloon Analog Risk Task (BART) The goal was to accumulate a maximum of points by pumping a series of 30 simulated balloons with a button press. The balloons could explode if participants reached a maximum pumping time fixed for each balloon. At any time during a trial, participants could stop pumping to save the amount of points accumulated. The average pumping time on unexploded balloons was interpreted as an index of risk-taking, where a greater time pumping indicated more risk-taking [8].

Driving performance assessment Participants performed a 30-minute on-road session with a professional driving instructor. The instructor filled a French version of the Test Ride for Investigating Practical Fitness to Drive (TRIP), which is a 62-item grid assessing multiple components of the task of driving [11]. Global score was standardized on a scale of 100. Four additional scores based on the hierarchical model of driving behavior by Michon [12] were calculated following the work of Ranchet et al. [11]: the operational score (11 items), related to immediate reactions such as braking; the tactical score (12 items), reflecting proactive components such as anticipation and safety distance; the tactical compensation score (7 items), investigating adaptive behaviors like the choice of speed; and the strategic compensation score, a 16-item questionnaire assessing the driving conditions that are usually avoided (e.g., high traffic, night driving).

Statistical analysis Linear mixed models were fitted to predict the driving performance with test variables as fixed effects and both age and monitor as random intercept effects.

RESULTS

Psychological tasks	Tests variables	Driving performance				
		Strategic compensation	Tactical	Tactical compensation	Operational	Global
Simon task	Mean reaction time (RT)	6.16*	2,55	0,01	12,97***	12,88***
	Error rate	0,02	0,97	0,11	0,11	0,85
	Interference effect	3.55.	0,57	0,28	3,01.	0,97
	Gratton effect	5,91*	0	0,05	1,75	0,27
Stop Signal task	SSRT	2,22	1,51	1,06	4,64*	1,64
BART	Average pumping time	4.03*	12,06***	3,08.	4,72*	10,68**

*Note. . = p<.10, *=p<.05, **=p<.01, ***=p<.001.*

Table 1: F-statistics of the ANOVAs for each test variable and driving score. Reaction time and error rate refer to performances obtained in the Simon task. The color code represents the direction of the significant effect (red and blue for positive and negative slopes, respectively).

Strategic compensation score increased in individuals showing higher mean RTs in the Simon task, but decreased in individuals showing higher Gratton effects or higher average pumping time at the BART. Tactical score was only predicted by the average pumping time: scores increased in individuals with higher risk-taking. Operational and global scores were smaller in individuals with higher RT and greater in individuals with higher average pumping time. Operational score also decreased with higher SSRT. Interestingly, the risk-taking index predicted the variance of almost all driving scores whereas out of the two inhibition measures (i.e interference effect and SSRT), only the SSRT predicted part of the driving performance.

DISCUSSION

The current study explored how objective scores obtained in psychological tests can predict the capacities necessary for safe driving. Higher risk-taking individuals showed better driving performances and less strategic avoidance of difficult situations. Unexpectedly, both motor inhibition and interference resolution failed to predict most of the driving performance. Risk taking tendency was however a high predictor of driving capacities.

This study showed that both types of inhibition assessed by the interference effect and the SSRT are limited in predicting driving capacity in an ecological setting. Although the executive functions are essential, our study suggests that testing them in a non-pathological population barely informs on the ability to drive. As long as executive functions are operational, personality factors such as risk-taking tendencies appear to be a much better evaluation criterion of the safety of the driving behavior.

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References:

[1] Richard Ridderinkhof, K., Forstmann, B. U., Wylie, S. A., Burle, B., & van den Wildenberg, W. P. (2011). Neurocognitive mechanisms of action control: resisting the call of the Sirens. Wiley Interdisciplinary Reviews: Cognitive Science, 2(2), 174-192.
[2] Anstey, K. J., Wood, J., Lord, S., & Walker, J. G. (2005). Cognitive, sensory and physical factors enabling driving safety in older adults. *Clinical psychology review*, *25*(1), 45-65.
[3] Asimakopulos, J., Boychuck, Z., Sondergaard, D., Poulin, V., Ménard, I., & Korner-Bitensky, N. (2012). Assessing executive function in relation to fitness to drive: A review of tools and their ability to predict safe driving. *Australian Occupational Therapy Journal*, *59*(6), 402-427.
[4] Vaca, F. E., Walthall, J. M., Ryan, S., Moriarty-Daley, A., Riera, A., Crowley, M. J., & Mayes, L. C. (2013). Adolescent Balloon Analog Risk Task and behaviors that influence risk of motor vehicle crash injury. *Annals of advances in automotive medicine*, *57*, 77.
[5] Cheng, A. S., Ng, T. C., & Lee, H. C. (2012). Impulsive personality and risk-taking behavior in motorcycle traffic offenders: A matched controlled study. *Personality and Individual Differences*, *53*(5), 597-602.
[6] Craft, J. L., & Simon, J. R. (1970). Processing symbolic information from a visual display: interference from an irrelevant directional cue. *Journal of experimental psychology*, *83*(3p1), 415.
[7] Logan, G. D., & Cowan, W. B. (1984). On the ability to inhibit thought and action: A theory of an act of control. *Psychological review*, *91*(3), 295.
[8] Lejuez, C. W., Read, J. P., Kahler, C. W., Richards, J. B., Ramsey, S. E., Stuart, G. L., ... & Brown, R. A. (2002). Evaluation of a behavioral measure of risk taking: the Balloon Analogue Risk Task (BART). *Journal of Experimental Psychology: Applied*, *8*(2), 75.
[9] Gratton, G., Coles, M. G., & Donchin, E. (1992). Optimizing the use of information: strategic control of activation of responses. *Journal of Experimental Psychology: General*, *121*(4), 480.
[10] Verbruggen, F., Aron, A. R., Band, G. P., Beste, C., Bissett, P. G., Brockett, A. T., ... & Colzato, L. S. (2019). A consensus guide to capturing the ability to inhibit actions and impulsive behaviors in the stop-signal task. *Elife*, *8*, e46323.
[11] Ranchet, M., Paire-Ficout, L., Uc, E. Y., Bonnard, A., Sornette, D., & Broussolle, E. (2013). Impact of specific executive functions on driving performance in people with Parkinson's disease. *Movement disorders*, *28*(14), 1941-1948.
[12] Michon, J. A. (1985). A critical view of driver behavior models: what do we know, what should we do?. In *Human behavior and traffic safety* (pp. 485-524). Springer, Boston, MA.

Processing traffic messages in autonomous driving

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Keywords: Audiovisual messages, Autonomous vehicles, Driving performance, Variable message signs.

ABSTRACT

Variable message signs (VMS) visually inform about unexpected and special traffic situations in the driving environment. However, the identification of the message on a VMS can be practically impossible in some circumstances, for example, if there are technical problems with the device, or in adverse environmental conditions. Research on in-vehicle systems shows that drivers can benefit from bimodal (audiovisual) messages [1]. Interestingly, there is evidence that drivers remember messages better if they are received through the auditory system than through the visual one, in particular, messages indicating the route to follow [2]. However, other results [3] do not support a possible general advantage of auditory messages over visual ones, nor an advantage of audiovisual messages over unimodal ones. In any case, these results, observed in the study of in-vehicle systems, might not generalize to the case of messages presented in VMS.

The main objective of this work was to study if bimodal (audio+visual) messages can contribute to improve the processing of VMS messages, as compared to only visual messages. Besides, we tested if autonomous driving would affect the processing of traffic messages displayed on VMS, particularly, whether drivers would be more capable to identify the critical messages when they were freed from the burden of manual control.

Two samples of 18 drivers, matched in gender and age, participated in two separated experiments in a Carnetsoft driving simulator. All participants held a Spanish B category driving license. The study was approved by the research ethics committee of the University of Valencia. In both experiments, there were two message conditions. In the visual one, only the text of the VMS was available. In the audio+visual condition, they heard the content of the VMS as an audio just before they could read the VMS text (a concurrent presentation of the audio and visual messages was discarded, to prevent possible interference effects that may lead the participants to focus on only one of them,

depending on their preferences). In the first experiment, participants drove manually and had to do two tasks. In the VMS-related task, they had to read the messages displayed on the VMS posted along the route, and to indicate (as soon as possible but without making errors) whether the message was providing information about irrelevant or potentially hazardous situations, by manually pressing the correct lever behind the steering wheel. At the same time, they had to do a car-following task, i.e., to keep a constant distance to the preceding car. In the second experiment, drivers activated the autonomous mode and only had to do the VMS-related task.

We analyzed the effects of this experimental manipulation of message condition (visual *versus* audio+visual messages) and driving mode (manual *versus* autonomous driving) on two aspects of the reading task performance: a) response accuracy, as measured by the percentage of correct responses to the VMS-related task, and b) response distance, i.e., the distance to the VMS when the driver gave the correct response. Response accuracy was analyzed using generalized linear mixed models with the package lme4 v1.1-5 [4] and implemented in R [5]. A model with a binomial distribution (logit): accuracy ~ driving mode * message condition + (1 | participant) was used. Response distance was analyzed by means of the traditional frequentist analysis of variance (ANOVA) with the IBM SPSS Statistics 24 software. In both cases, the variable message condition was included as an intra-subject factor (visual *versus* audio+visual), and the variable driving mode, as an inter-subject factor (manual *versus* autonomous driving).

No interaction was found between message condition and driving mode in the mean response distances. However, the main effects of driving mode, $F(1, 34) = 7.27$, $p = .011$, $\eta^2 = .176$, and message condition, $F(1, 34) = 745.91$, $p < .001$, $\eta^2 = .956$, were statistically significant (see Table 1). We also found no interaction between the two variables in accuracy, but the main effects were significant. For driving mode, Estimate = 1.37, SE = 0.62, $z = 2.22$, $p = .027$, and for message condition, Estimate = 1.37, SE = 0.57, $z = 2.40$, $p = .017$ (see Table 1). On the one hand, the audio+visual condition was better than the visual one, both in response accuracy and response distance. On the other hand, response accuracy in the reading task was slightly better in the autonomous driving mode than in the manual one. Nevertheless, participants responded to the messages at longer (i.e., safer) distances to the VMS when driving manually.

Driving mode	Message condition	Accuracy (%)	SD	CI 95%		Mean response distance	SD	CI 95%	
Manual	Visual	95.73	2.03	93.05	97.59	103.1	24.3	92.7	113.4
	Audio+visual	98.85	1.07	97.09	99.69	180.9	13	175.7	186.2
Autonomous	Visual	98.84	1.07	97.32	99.62	86.7	18.7	76.3	97.1
	Audio+visual	99.31	0.83	97.98	99.86	170.9	8.5	165.6	176.2

Table 1. Accuracy (%) and response distance (m). Note: SD = Standard Deviation; CI 95% = Lower (left) and higher (right) values of the 95% Confidence Interval

Regarding the advantage of the audio+visual condition, these results replicate the findings by [6]. Concerning the differences between autonomous and manual driving, the autonomous driving was associated with delayed, although slightly more accurate responses in the VMS-related task. This suggests that the autonomous mode, despite relieving the driver from the burden of vehicle control, was not associated with an early identification of the VMS message. The significant reduction of response distances in the autonomous mode implies that drivers might partially disregard the processing of messages displayed on VMS. One explanation for this disregard for the VMS could be related with the phenomenon called "mind-wandering", reported by other authors [7] when comparing manual *versus* autonomous driving. It could be that our participants suffered "mind-wandering" and this made them to react later. In addition, the increased accuracy observed in the autonomous mode might be a consequence of a trade-off with the response distance variable, i.e., drivers responding later had more time to process the traffic messages and, in addition, legibility of the VMS was better at shorter distances.

The present results come from a relatively simple task (short predictable messages and responses and no complex interaction with other vehicles). Consequently, further studies would be required to assess the practical relevance of these results in real, more complex driving situations. All in all, the current study provides new evidence about the influence of autonomous driving, in particular, when processing messages on VMS.

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References:

[1] Ghirardelli, T. G., & Scharine, A. A.: 'Auditory-visual interactions'. In Rash, C.E., Russo, M.B., Letowski, T.R., Schmeisser, E.T. (Ed.): 'Helmet-mounted displays: Sensation, perception and cognition issues' (U.S. Army Aeromed. Res. Laborat., 2009, 1st edn.), pp. 599-618

[2] Dalton, P., Agarwal, P., Fraenkel, N., et al.: 'Driving with navigational instructions: Investigating user behaviour and performance'. Accid. Anal. Prev., 2013, 50, pp. 298-303

[3] Wickens, C. D., & Gosney, J. L.: 'Redundancy, Modality, Priority and Instructions in Dual Task Interference Between Simulated Vehicle Control and In-Vehicle Technology'. Tec. Rep., 2003

[4] Bates, D., Maechler, M., Bolker, B., et al.: 'Fitting Linear Mixed-Effects Models Using lm4', Jour. Stat. Soft., 2015, 67, pp 125-138

[5] R Core Team: 'R: A Language and Environment for Statistical Computing', R Foundation for Statistical Computing

[6] Tejero, P., Pi-Ruano, M., Roca, J.: 'Better read it to me: Benefits of audio versions of variable message signs in drivers with dyslexia'. Ann. Dysl., 2020, 70, (3), pp. 295-312

[7] Hidalgo-Muñoz, A. R., Jallais, C., Evennou, M., et al.: 'Hemodynamic responses to visual cues during attentive listening in autonomous versus manual simulated driving: A pilot study', Brain Cogn., 2019, 135

Drivers' Mobile Phone Use during COVID-19: Motivating Factors and Implications

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Keywords: Boredom, COVID-19, Driver Distraction, Habitual Phone Use, Mobile Phone, Safety

ABSTRACT
Phone use while driving has been a significant public health and safety challenge at the global level [1]. Many psychosocial, societal, and environmental factors as well as demographic variables have been linked to frequency of phone use while driving [2]. For example, boredom and habitual phone use are positively related to increased phone use while driving for young men; however, daily frequency of phone use positively predicted phone use while driving for young women [3]. Drivers also report phone use while driving as a strategy to alleviate boredom and drowsiness while having social interactions with others [4].

The COVID-19 pandemic has disrupted our daily routines in unprecedented ways. Data collected in the early phase of the pandemic (February-April, 2020), when many nations started to impose lockdown and stay-at home orders, indicated trends of reduced driving and traffic volumes but increased driving speeds, more frequent strong acceleration and braking, and increased phone use while driving [5], [6]. These changes may be motivated by anxiety due to uncertainty about the future, need for entertainment, news, and social interactions, individual differences, and changes of traffic patterns, just to name a few. The current study aimed to shed some light on one of the open questions, that is, to evaluate the motivating factors for phone use while driving during the pandemic with the purpose of replicating findings [3] from a non-pandemic period.

Data was collected via Amazon Mechanical Turk during the week of April 20, 2020. Individuals who held the status of a Mechanical Turk master, was an adult, and resided in the USA were eligible to participate. This study received the Institution Review Board approval from the author's university. The survey items were programed in Qualtrics and included several validated psychosocial scales: The Need to Belong Scale [7], the Fear of Missing Out Scale [8], Perceived Attachment to Phone Scale [9], Habitual Smartphone and Internet Behavior Scale [10], [11], the Self Regulation Scale [12], the Boredom Proneness Scale [13], [14], and the Abbreviated version of the Big Five Inventory [15]. The rest of the survey items are detailed below:

(A) *Mobile Phone Use While Driving* items. These questions were about the frequency of using mobile phones or smartphones while driving, and the phone applications (e.g., texting, GPS, etc.) typically used while driving. These questions were presented twice—for participants to indicate their answers from two time periods: before the pandemic and now during the pandemic. (B) *Information and Communications Technology (ICT)* items. ICT was defined as "the integration of telecommunications and computers as well as necessary software, hardware, and audiovisual systems that enable users to access, store, transmit, and manipulate information and to communicate in a digital form." These questions were about the time spent using ICTs for getting news on a daily basis. These questions were also presented twice—before the pandemic and now during the pandemic. (C) *Demographic Questionnaire* items. There were 16 questions that asked for participants' age, gender, when they obtained their driver's license, whether they had a valid license now, residence, race and ethnicity, education, income, employment status, weekly frequency of driving before and during the pandemic, annual mileage, number of accidents in the

past 3 years, frequency of using seat belt, and whether they heard of autonomous vehicles. (D) *Attention Check Questions*. Three attention check questions were used to help identify inattentive participants and to provide progress status, as they appeared after each quarter (1/4, 1/2, and 3/4) in the survey.

On average, participants took 16 minutes to complete the survey. Eight of the participants provided at least one invalid answer to the three attention check questions and were removed from the dataset; therefore, the final sample size was 394, with 219 men and 175 women and ages ranging from 20 to 76. SPSS version 26 was used for the analyses. Correlations of the variables were check and there was no evidence of multicollinearity (all the Spearman correlation coefficients were smaller then .6). The frequency of phone use while driving variable was dichotomized to reflect a low (fewer than 1) and high (more than 2) frequency of use out of 5 trips.

The first logistic regression was used to model the relationship between frequency of phone use while driving (low vs high) and the psychosocial, ICT use, and demographic variables *before* the pandemic. These variables were entered in three blocks, with block 1 consisting of psychosocial variables, block 2 consisting of ICT use variable, and block 3 consisting of demographic variables. Insignificant variables were removed with each iteration. The final model had Nagelkerke R of .24 and Hosmer and Lemeshow Test of χ^2 (8, N = 394) = 7.60, p = .47, indicating good fit to the data. The model had an overall accuracy of 70.20%. For each one-point increase on ratings of boredom proneness, need to belong, number of phone application used before pandemic, and number of accidents, there were odds of higher frequency of phone use while driving by a multiplicative factor of 1.04, 1.03, 1.32, and 1.93, respectively. Younger individuals and individuals with higher incomes were 1.03 and 1.37 times, respectively, more likely to report higher frequency of phone use while driving. Interestingly, for each one-point increase on ratings of habitual internet use, there were odds of 1.76 times lower frequency of phone use while driving.

The second logistic regression was used to model the relationship between frequency of phone use while driving and the psychosocial, ICT use, and demographic variables *during* the pandemic. The same modeling approach was used. The final model had Nagelkerke R of .30 and Hosmer and Lemeshow Test of χ^2 (8, N = 394) = 9.49, p = .30, indicating good fit to the data. The model had an overall accuracy of 77.10%. For each one-point increase on ratings of boredom proneness, habitual smartphone use, number of phone application used during pandemic, and number of accidents, there were odds of higher frequency of phone use while driving by a multiplicative factor of 1.05, 1.43, 1.43, and 2.24, respectively. In addition, younger individuals and individuals with higher income were 1.05 and 1.25 times, respectively, more likely to report higher frequency of phone use while driving. However, for each one-point increase on ratings of habitual internet use, there were odds of 2.47 times lower frequency of phone use while driving.

These findings supported the links between boredom and phone use while driving [3] as well as between social interactions and phone use while driving [4] that were observed prior to the pandemic. Our finding also supported the link between phone use while driving and age and income [16]. One surprising finding was the association between higher habitual internet use and lower phone use while driving from this sample. While the benefits of internet use on stronger perceived social support and decreased loneliness have been documented [17], its impact on other types of social interaction activities, such as phone use while driving, should be further examined. Overall, the current results indicated some consistency, at least based on participant recalls and self-reports, in phone use while driving patterns and motivating factors during the two periods – before and during the pandemic.

References

[1] World Health Organization and National Highway Traffic Safety Administration, “Mobile phone use: A growing problem of driver distraction,” World Health Organization, Geneva, 2011. Accessed: Oct. 24, 2018. [Online]. Available:

http://apps.who.int/iris/handle/10665/44494.
[2] J. K. Caird, S. M. Simmons, K. Wiley, K. A. Johnston, and W. J. Horrey, “Does talking on a cell phone, with a passenger, or dialing affect driving performance? An updated systematic review and meta-analysis of experimental studies,” *Hum. Factors*, vol. 60, no. 1, pp. 101–133, Feb. 2018, doi: 10.1177/0018720817748145.
[3] J. Oxtoby, R. Schroeter, D. Johnson, and S.-A. Kaye, “Using boredom proneness to predict young adults’ mobile phone use in the car and risky driving,” *Transp. Res. Part F Traffic Psychol. Behav.*, vol. 65, pp. 457–468, Aug. 2019, doi: 10.1016/j.trf.2019.08.008.
[4] T. Iseland, E. Johansson, S. Skoog, and A. M. Dåderman, “An exploratory study of long-haul truck drivers’ secondary tasks and reasons for performing them,” *Accid. Anal. Prev.*, vol. 117, pp. 154–163, Aug. 2018, doi: 10.1016/j.aap.2018.04.010.
[5] C. Katrakazas, E. Michelaraki, M. Sekadakis, and G. Yannis, “A descriptive analysis of the effect of the COVID-19 pandemic on driving behavior and road safety,” *Transp. Res. Interdiscip. Perspect.*, vol. 7, p. 100186, Sep. 2020, doi: 10.1016/j.trip.2020.100186.
[6] D. Stavrinos *et al.*, “Adolescent driving behavior before and during restrictions related to COVID-19,” *Accid. Anal. Prev.*, vol. 144, p. 105686, Sep. 2020, doi: 10.1016/j.aap.2020.105686.
[7] M. R. Leary, K. M. Kelly, C. A. Cottrell, and L. S. Schreindorfer, “Construct validity of the need to belong scale: Mapping the nomological network,” *J. Pers. Assess.*, vol. 95, no. 6, pp. 610–624, Nov. 2013, doi: 10.1080/00223891.2013.819511.
[8] A. K. Przybylski, K. Murayama, C. R. DeHaan, and V. Gladwell, “Motivational, emotional, and behavioral correlates of fear of missing out,” *Comput. Hum. Behav.*, vol. 29, no. 4, pp. 1841–1848, Jul. 2013, doi: 10.1016/j.chb.2013.02.014.
[9] J. A. Weller, C. Shackleford, N. Dieckmann, and P. Slovic, “Possession attachment predicts cell phone use while driving,” *Health Psychol.*, vol. 32, no. 4, pp. 379–387, 2013, doi: 10.1037/a0029265.
[10] A. J. A. M. van Deursen, C. L. Bolle, S. M. Hegner, and P. A. M. Kommers, “Modeling habitual and addictive smartphone behavior: The role of smartphone usage types, emotional intelligence, social stress, self-regulation, age, and gender,” *Comput. Hum. Behav.*, vol. 45, pp. 411–420, Apr. 2015, doi: 10.1016/j.chb.2014.12.039.
[11] M. Limayenm, S. Hirt, and C. Cheung, “Habit in the context of IS continuance: Theory extension and scale development,” *ECIS 2003 Proc.*, Jan. 2003, [Online]. Available: https://aisel.aisnet.org/ecis2003/90.
[12] M. Diehl, A. B. Semegon, and R. Schwarzer, “Assessing attention control in goal pursuit: A component of dispositional self-regulation,” *J. Pers. Assess.*, vol. 86, no. 3, pp. 306–317, Jun. 2006, doi: 10.1207/s15327752jpa8603_06.
[13] R. Farmer and N. D. Sundberg, “Boredom proneness–The development and correlates of a new scale,” *J. Pers. Assess.*, vol. 50, no. 1, pp. 4–17, Mar. 1986, doi: 10.1207/s15327752jpa5001_2.
[14] S. J. Vodanovich, J. C. Wallace, and S. J. Kass, “A confirmatory approach to the factor structure of the Boredom Proneness Scale: Evidence for a two-factor short form,” *J. Pers. Assess.*, vol. 85, no. 3, pp. 295–303, Dec. 2005, doi: 10.1207/s15327752jpa8503_05.
[15] B. Rammstedt and O. P. John, “Measuring personality in one minute or less: A 10-item short version of the Big Five Inventory in English and German,” *J. Res. Personal.*, vol. 41, no. 1, pp. 203–212, Feb. 2007, doi: 10.1016/j.jrp.2006.02.001.
[16] A. S. Nurullah, J. Thomas, and F. Vakilian, “The prevalence of cell phone use while driving in a Canadian province,” *Transp. Res. Part F Traffic Psychol. Behav.*, vol. 19, pp. 52–62, Jul. 2013, doi: 10.1016/j.trf.2013.03.006.
[17] L. H. Shaw and L. M. Gant, “In defense of the Internet: The relationship between Internet communication and depression, loneliness, self-esteem, and perceived social support,” *Cyberpsychol. Behav.*, vol. 5, no. 2, pp. 157–171, Apr. 2002, doi: 10.1089/109493102753770552.

Driver State Monitoring – Inferring Driver Anger and Attention from Electromyography

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ABSTRACT

Driver anger – characterized as a personality trait related to driving and the predisposition to experience anger frequently and intensely across situations [1] – has been linked to increased crash risk [2]. Recently, efforts have been made to detect angry driving behaviors and anger-provoking traffic situations early enough so that timely and affective mitigation strategies can be implemented to improve driver emotions [3]. For example, music, voice, and ambient light, have been experimented and found to have some effect on decreasing driver anger [3], [4].

One way to monitor the changes in driver anger and other emotional states is through the collection of drivers' physiological signals, such as heart rate, skin conductance, respiration rate, and characteristics of electroencephalography and electromyography (EMG) [5]. While the association between facial EMG and emotional expressions has been studied in experimental psychology [6], [7], this biosensing approach is new to the driving context. One of the primary facial muscles associated with negative emotion, frustration, and anger, is the corrugator supercilia, which is also responsible for producing frowns [8]. The goal of this research was to investigate the relationship between the corrugator supercilia activations through facial EMG and driver anger, while using self-reported emotions as confirmation. The results of this research are expected to establish feasibility of inferring driver anger and affective state through facial EMG sensing and monitoring.

This initial proof-of-concept study took place in a driving simulator environment and investigated three hypotheses: 1) Corrugator supercilia activation would increase during anger-provoking driving events when compared to baseline. 2) Upon experiencing anger-provoking events, participants would report higher levels of subjective anger when compared to baseline. 3) Participants who scored higher on trait driving anger would experience greater feelings of anger upon experiencing anger-provoking events than participants with lower trait driving anger.

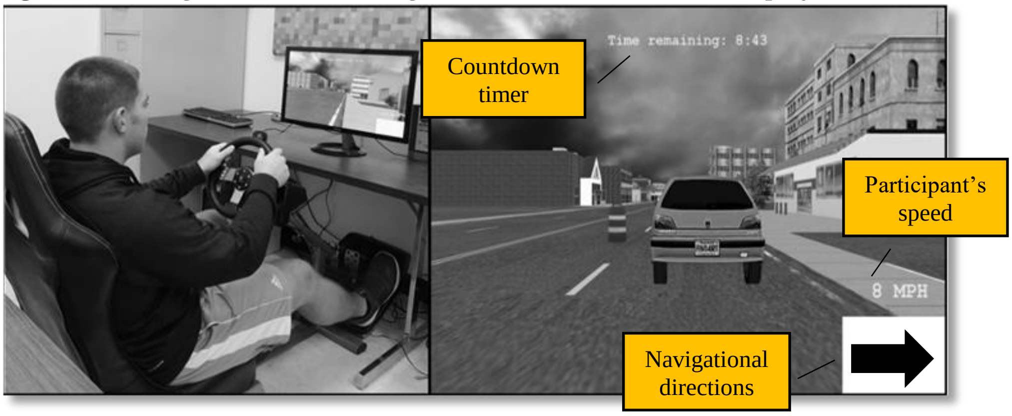
The driving simulator used in the current study was a Realtime Technologies desktop simulator comprised of driver's seat, pedals, and a Logitech steering wheel. The simulation was displayed on a 1920x1080 desktop monitor. The simulated environment was built with SimVista and SimCreator software. The driving environment included rural and urban settings with variations of buildings, trees, straight and curved roads, intersections, and construction zones. In total, participants completed three drives: the training drive allowed the participant to familiarize themselves with the driving simulator, and two experimental drives—a control drive and an event drive. The order of the experimental drives was counter-balanced to prevent order effects.

Facial electromyography (EMG) data were collected via a BIOPAC MP 150 system with the Electromyogram Amplifier (EMG100C). The EMG was set to a sample rate of 1000/second, gain at 2000, and 100HzHP (OFF) & 500HzLP. The electrodes used were BIOPAC EL513 – disposable cloth electrodes designed for facial EMG. EMG data were collected and processed using AcqKnowledge 4.3 software. Two shielded electrodes were placed on the area of the corrugator supercilia (+/-) and a ground electrode placed just below the cheekbone, in accordance with the established research protocol [9].

The Driving Anger Scale (DAS) [1] (14-item on a scale of 1-5, reliability of .80) was used to measure the general trait driving anger. The Discrete Emotions Questionnaire (DEQ) [10] was used to measure basic emotions, such as anger, sadness, and happiness on a scale of 1-7. The DEQ was administered four times throughout the study and served as a manipulation check. A demographic questionnaire was used to collect age, gender, and years of driving experience. A motion sickness screening questionnaire was used to screen out participants who may be susceptible to experiencing motion sickness symptoms.

Anger was induced through the use of traffic events, navigation directions, and time pressure. There were 12 anger-provoking traffic events [11] in the event drive and we reasoned that with repeated exposure, the feelings of negative emotions (e.g., anger) would be compounded. These events were placed throughout the entire event drive but occurred more frequently in the beginning of the drive to invoke an effect earlier in the experiment. For comparison purposes, the control drive had identical road network and ambient traffic, but did not have any anger-provoking events. Navigational directions were provided to participants in the form of a directional arrow in the white box in bottom right of the simulator display (Figure 1). Turn by turn directions were provided when participants approached intersections, for the purpose of directing them through a preprogrammed path. Alternate routes were built into the environment which would allow participants to recover from a missed turn. Time pressure was manipulated via a countdown timer shown at the top of the simulator display (see Figure 1), for the purpose of creating a sense of urgency for completing the experimental drives. If participants did not finish the drives within 10 minutes, a message would appear and ask participants to stop the car.

Figure 1. Configurations of Driving Simulator and Simulator Display.



Upon entering the lab, participants were directed to read and sign a consent form. Then, participants were verbally administered a motion sickness screening questionnaire and completed DAS and the demographic questionnaire. Next, participants sat in the driver's seat of the simulator, while an experimenter attached EMG electrodes to their respective locations on the participants' faces. A 2-minute baseline EMG recording was then conducted while participants sat quietly. The participants then completed the DEQ. Participants were read the instructions and proceeded to complete the training drive, which lasted for 5 minutes. Included in the instructions, participants were told to assume they are driving in an unfamiliar place, to abide by all traffic laws, avoid collisions, and follow the speed limit of 20 mph. Participants then completed the DEQ the second time. Half of the participants then proceeded to experience the control drive, complete the DEQ the third time, and then experience the event drive. The other half of the participants experienced the event drive, complete the DEQ, and then experience the control drive. Once the second experimental drive was completed, participants completed the DEQ the fourth time. On average, participants took 40-50 minutes to complete the experimental procedures.

A total of 22 participants (10 females) were recruited, with the mean age being 22.1 (SD = 5.3) and years of driving experience being 5.5 years (SD = 5.4). The dependent variables of this research were trait driving anger, facial EMG activations, and self-reported emotions. EMG values were analyzed using AcqKnowledge 4.3, the raw EMG was processed using the root mean square at an interval of 0.03 seconds. Data analysis is on-going and will be completed before the conference.

References

[1] J. L. Deffenbacher, E. R. Oetting, and R. S. Lynch, "Development of a Driving Anger Scale," *Psychol. Rep.*, vol. 74, no. 1, pp. 83–91, Feb. 1994, doi: 10.2466/pr0.1994.74.1.83.

[2] L. Precht, A. Keinath, and J. F. Krems, "Effects of driving anger on driver behavior – Results from naturalistic driving data," *Transp. Res. Part F Traffic Psychol. Behav.*, vol. 45, pp. 75–92, Feb. 2017, doi: 10.1016/j.trf.2016.10.019.

[3] M. Braun, J. Schubert, B. Pfleging, and F. Alt, "Improving driver emotions with affective strategies," *Multimodal Technol. Interact.*, vol. 3, no. 1, p. 21, Mar. 2019, doi: 10.3390/mti3010021.

[4] Y. Zhu, Y. Wang, G. Li, and X. Guo, "Recognizing and releasing drivers' negative emotions by using music: Evidence from driver anger," in *Adjunct Proceedings of the 8th International Conference on Automotive User Interfaces and Interactive Vehicular Applications*, New York, NY, USA, Oct. 2016, pp. 173–178, doi: 10.1145/3004323.3004344.

[5] P. Wan, C. Wu, Y. Lin, and X. Ma, "On-road experimental study on driving anger identification model based on physiological features by ROC curve analysis," *IET Intell. Transp. Syst.*, vol. 11, no. 5, pp. 290–298, Mar. 2017, doi: 10.1049/iet-its.2016.0127.

[6] Y. Golland, A. Hakim, T. Aloni, S. Schaefer, and N. Levit-Binnun, "Affect dynamics of facial EMG during continuous emotional experiences," *Biol. Psychol.*, vol. 139, pp. 47–58, Nov. 2018, doi: 10.1016/j.biopsycho.2018.10.003.

[7] J. Künecke, A. Hildebrandt, G. Recio, W. Sommer, and O. Wilhelm, "Facial EMG responses to emotional expressions are related to emotion perception ability," *PLOS ONE*, vol. 9, no. 1, p. e84053, Jan. 2014, doi: 10.1371/journal.pone.0084053.

[8] J.-W. Tan *et al.*, "Recognition of intensive valence and arousal affective states via facial electromyographic activity in young and senior Adults," *PLOS ONE*, vol. 11, no. 1, p. e0146691, Jan. 2016, doi: 10.1371/journal.pone.0146691.

[9] A. J. Fridlund and J. T. Cacioppo, "Guidelines for human electromyographic research," *Psychophysiology*, vol. 23, no. 5, pp. 567–589, 1986, doi: https://doi.org/10.1111/j.1469-8986.1986.tb00676.x.

[10] C. Harmon-Jones, B. Bastian, and E. Harmon-Jones, "The Discrete Emotions Questionnaire: A New Tool for Measuring State Self-Reported Emotions," *PLOS ONE*, vol. 11, no. 8, p. e0159915, Aug. 2016, doi: 10.1371/journal.pone.0159915.

[11] Y.-C. Lee and F. K. Winston, "Stress induction techniques in a driving simulator and reactions from newly licensed drivers," *Transp. Res. Part F Traffic Psychol. Behav.*, vol. 42, Part 1, pp. 44–55, Oct. 2016, doi: 10.1016/j.trf.2016.06.019.

List of participants

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- Berthelon Catherine
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- Böhm Manuel
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- Bruno Giovanni
- Bruyas Marie-Pierre
- Bucsuházy Kateřina
- Ceci Ruggero
- Clifford William
- Cooper Naomi
- Cornelia Hollander
- Cortez Diego
- Ćelić Matea
- Dabic Stephanie
- El Ghoulti Isabelle
- Flety Duprey Jeanne
- Fort Alexandra
- Forzy Jean-François
- Fredriksson Rikard
- Garcia Quinteiro Eva
- Geeraerts Elien

- Geeraerts Elien
- Gershon Pnina
- Grisetto Fanny
- Gunnarsson Tony
- Harries Brett
- Hasan Aamir
- Hertach Patrizia
- Isaksson Hellman Irene
- Jackson James
- Jallais Christophe
- Jaussein Marie
- Johansson Emma
- Kärner-Rebane Katrin
- Kircher Katja
- Kujala Tuomo
- Large David
- Le Denmat Pierre
- Lee Yi-Ching
- Liu Zhuofan
- Ljung Aust Mikael
- Maif Fondation
- Manawadu Udara
- Mars Franck
- Marti Paul
- Mcdonnell Amy
- Mehler Bruce
- Menas Soren
- Mendoza Lucile
- Morgenstern Tina
- Nambiar Hitesh
- Nemoto Hiromi
- Nilsson Emma

- Oikonomou Maria
- Perrotte Gaëtan
- Pi-Ruano Marina
- Pipkorn Linda
- Ponte Giulio
- Portron Arthur
- Riguelle François
- Roger Clémence
- Rosman Alexandra
- Sagesjö Marjukka
- Sano Masataka
- Sato Toshihisa
- Seaman Sean
- Sepp Liis
- Sevcenko Natalia
- Shiferaw Brook
- Stelling Agnieszka
- Tallo Kerli
- Tattegrain Helene
- Tejero Maria Del Pilar
- Toman Mikuláš
- Verboven Vincent
- Viström Matias
- Wörle Johanna
- Wundersitz Lisa
- Yutaro Tsugawa

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