Pupil size indicators of task interactions during driving

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Introduction and Goal

Driving is a complex task that requires the management of multiple sub-tasks. An important aspect of managing subtasks is the working memory load (WML), which has been linked to driving performance through its impact on decision making (Ross et al., 2015, 2018). An example when WML impacts decision making is turning at unsignaled crossings where drivers have to continuously integrate and dynamically update information about the traffic participants in the environment while making decisions (de Waard 1996, da Silva 2014). This leads to different cognitive demands being concurrently imposed on the driver. Some of these tasks could possibly draw from a shared set of cognitive resources leading to a potential interaction between subtasks. Since cognitive capacity is limited it is not surprising that many traffic accidents are caused by poor decision making by overwhelmed drivers, whose capacity has been exhausted (Borghini, 2014). Pupil diameter has been shown to be a relevant proxy of internal cognitive and attentional states in laboratory settings, while its real world usefulness is being further investigated (Peysakhovich et al. 2018). In this study, we demonstrate interactions between WML and decision making while driving using task-evoked pupillary responses (TEPRs) accompanying the decision making process.

Methods and Data Analysis

We collected data from 13 participants (6 males), aged 22-57 years (mean ± SD = 28.53 ± 9.55). Participants were told that they would receive a monetary reward if they managed to finish the driving block within a given time limit while avoiding risky driving maneuvers. On their way, participants were repeatedly confronted with a left-lane turning situation at unsignalized intersections where they had to decide to turn in front of an oncoming stream of vehicles (50 km/h). Gap sizes in the oncoming traffic were varied, with the first two gaps always being too short for turning (20m) and subsequent gap sizes ranging between 20m and 80m (step size 10m). This forced the participants to stop at the intersection and observe the oncoming traffic before deciding to turn. Once a decision to turn was made, participants reported the event through a button press. The given time limit and the traffic density within the intersection were designed such that participants had to turn quickly to finish the block in time to receive the bonus, thus forcing a decision to turn in front of an oncoming vehicle. We define the six second intervals around the button press (-3s to + 3s) as the decision making phase and the intervals between the decision making phases as the driving phase. Throughout the whole experimental block, participants continuously performed an additional n-back working memory task (0-back and 2-back) in parallel, to manipulate WML at low and high levels. Pupil data was z-score normalized and average TEPRs following decision making were calculated for each participant. TEPR magnitudes were computed as the difference between the last minimum pupil size before decision making and the first maximum pupil size after decision making as indicated in Figure 1A and B. We report the number of errors in the n-back during decision making relative to the driving phase (Figure 1A). We excluded two participants from the analysis. One had no interpretable TEPR and the other had zero errors in the n-back task.

Results

We analyzed TEPR magnitude across n-back tasks and found that when plotting the TEPR magnitudes normalized by individual variance against n-back errors (Figure 1A) that the data fall into two clusters, which we confirmed using hierarchical clustering. Mean normalized TEPR magnitudes were significantly different ($t(9) = 6.01$, p=.0002) between clusters. Moreover, participants with smaller TEPR magnitudes (see Figure 1C for an example) maintained the n-back error rate from the driving phase during the decision making phase, while participants with larger TEPR responses (see Figure 1B for an example) had significantly increased error rates ($t(9) = 3.00$, $p = .0151$) (Figure 1, A). This indicates an interaction between the WM demands imposed by the n-back task and the decision making task as reflected in the TEPR magnitude during the decision making phase. We found neither a correlation between TEPR magnitudes and gap size during decision making nor a correlation between n-back level on TEPR magnitudes.

Discussion and Conclusion

The interaction between the TEPR magnitude and the increase in n-back error probability during the decision making phase indicates greater task prioritisation for the turning maneuver as compared to the n-back task in participants with larger TEPR magnitudes. This indicates that TEPRs analyzed around the time of decision making provide insight into strategies employed by participants to cope with the concurrent demands of the decision making and the n-back task. One additional observation that requires further investigation is the steadily increasing pupil-size leading up to the decision making phase, that could potentially reflect recruitment of cognitive resources in preparation for the decision making phase (Figure 1, B and C, 0-7s).

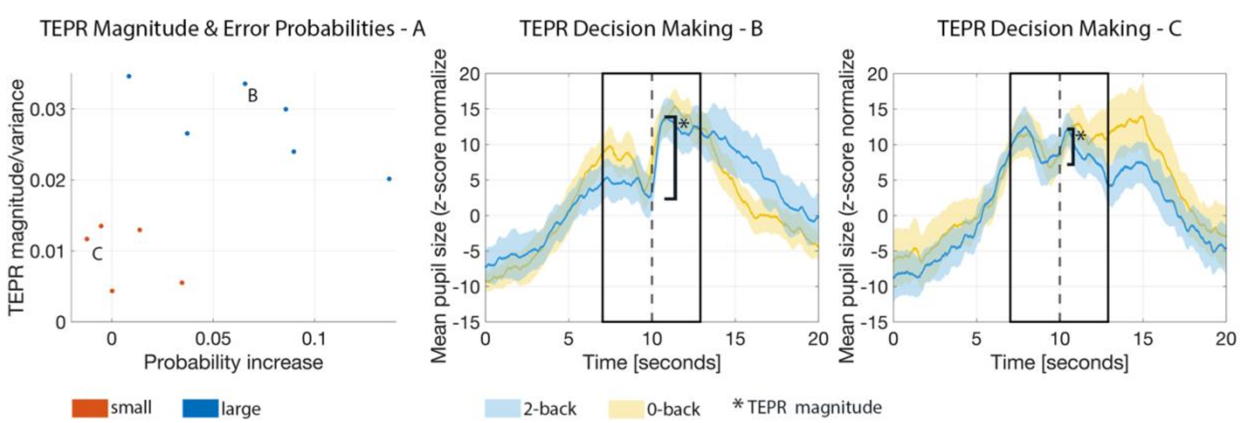

Figure 1. A shows the relationship between TEPR magnitude and the increase in the n-back task error probabilities during decision making relative to driving. B and C show average TEPR's from two example participants around the time of turning at the crossing. Shaded areas represent the 95% confidence intervals. The box indicates the decision interval from 7 to 13 seconds and TEPR magnitude is indicated as well. B is an example for a large TEPR magnitude and C for a small TEPR. The vertical line represents the time point of the button press indicating the decision to turn.

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