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Predicting Working Memory Load and Visuospatial Demands During Driving Using Eye-Tracking

Bachelor's Project Thesis

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Abstract: In adaptive driving, control over the vehicle is dynamically divided between the driver and an intelligent system. In order to develop a system that adapts its degree of control to the mental state of the driver, a robust method of measuring their cognitive load is required. This study focuses on pupillometry as a possible predictor for cognitive load, which is here defined as a combination of working memory load (WML) and visuospatial demands. We expected to find a positive correlation between cognitive load and pupil size. Additionally, we were interested in the effect of cognitive load on speed-keeping efforts, as measured by eye fixations on the speedometer. We expected to find a negative correlation between cognitive load and speedometer checking.

To investigate this, a simulated-driving experiment with eye-tracking was conducted in which WML and visuospatial demands were manipulated separately. In the simulation participants drove on a straight highway for 60 minutes. WML was manipulated by an n-back task ($n = 0, 1, 2, 3, 4$), performed by means of speed regulation. Visuospatial demands were manipulated by a change in the driving environment: a construction site with reduced lane width, increasing driving difficulty.

Results indicate that pupil size is a predictor for WML, but not for visuospatial demands. We conclude that in order to fully capture cognitive load while driving, pupillometry should be used in combination with a measure of visuospatial demands. Moreover, a negative correlation between WML and number of fixations on the speedometer was found. This highlights speed-keeping aid as an application for adaptive automation based on cognitive load.

1 Introduction

Driving a car is a challenging task. It involves processing a large number of stimuli and constantly updating a mental model of the environment. Not to mention, operating a vehicle requires making appropriate decisions to ensure the safety of both the driver and other road users. Driving is even more challenging for young and novice drivers. They are more prone to a high level of mental workload than experienced drivers due to their low level of operating skills, lack of driving experience (Gregersen & Bjurulf, 1996) and not fully-matured prefrontal cortex (Ross et al., 2014). This in turn is one of the causes for the relatively large number of traffic accidents that young drivers are involved in (Sena et al., 2013). And indeed, more generally, human failure is the cause of the majority of traffic accidents (De Waard, 1996).

An often proposed solution to this issue is automated driving, which refers to the vehicle being operated by an intelligent system (Cabrall, Janssen, & De Winter, 2018). However, human supervision is necessary even in fully automated driving to handle abnormal situations (Brookhuis & De Waard, 2007). Situations where the human operator must suddenly take back manual control then pose a serious risk. The driver is likely to respond inadequately due to their reduced attentional awareness and the erosion of their operating skills (Dijksterhuis, Stuiver, Mulder, Brookhuis, & De Waard, 2012). This is where adaptive automation comes into play.

In adaptive automation the division of control between the machine and the human operator is not static. Rather, it is based on changes in the physical environment or the condition of the operator (Sheridan, 2011). An important facet of this is adaptive automation based on the human factor of mental workload. An intelligent car that counteracts the negative effects of a high cognitive load on driving performance can greatly benefit the driver's safety.

We must first ask what the concept of cognitive load means. Let us define cognitive load as the level of perceived cognitive effort when performing a task. Two elements to cognitive load are most important in the context of driving: *central* and *visual* demands (De Waard, 1996).

Central demands have to do with working memory load (WML). In driving, working memory plays an important role in remaining focused on the task at hand; in other words, maintaining cognitive control (Wood, Hartley, Furley, & Wilson, 2016). It is also important in maintaining task goals, whether high-level (e.g., planning a route) or low-level (e.g., planning an overtaking manoeuvre).

The task of driving has some intricate visual demands as well. Visuospatial attention is required to process the movement of objects in traffic such as cars, pedestrians and traffic signs (Zheng, Yang, Easa, Lin, & Cherchi, 2020). This is a reflected by a number of studies on road accidents, linking reduced visuospatial attentional abilities –due to for example old age– to deteriorating driving performance (for a review see Owsley & McGwin, 2010). In practice, the requirement of visuospatial attention means that drivers must continuously scan their environment since criticial visual events can occur anywhere at any time.

In order to develop a system that adapts to the driver's cognitive load it is essential to find a robust method of measuring cognitive load. Changes in an individual's cognitive load are reflected by a number of physiological measures including heart rate variability, brainwave levels (as measured by for example an electroencephalogram, EEG), skin galvanic response and pupillary response (Haapalainen, Kim, Forlizzi, & Dey, 2010). The current study focuses on the latter as a predictor for cognitive load. We attempt to find whether the current level of cognitive load, defined as a combination of working memory load and visuospatial demands, can be predicted by pupil size.

Following results by Palinko, Kun, Shyrokov, and Heeman (2010) we expect that pupillometry can provide a viable estimation for cognitive load while driving. Furthermore, results by Scheunemann, Unni, Ihme, Jipp, and Rieger (2019) suggest an interaction between central and visual demands during driving at the brain level. This interaction effect between the two components of cognitive load is expected to be reflected in pupil size.

Additionally, we are interested in the effect of cognitive load on speed-keeping. A relationship between cognitive load and speed-keeping performance would reveal that speed-keeping is a necessary application of adaptive automation. That is, if a high cognitive load leads to diminished speed-keeping performance, then adaptive automation should aid the driver with keeping their speed when under high load. In this study we will use eye fixations on the speedometer as a measure of speed-keeping efforts. We therefore ask whether the number of eye fixations on the speedometer correlates with the current level of cognitive load.

Based on the notion of limited cognitive resources (as described by De Waard (1996)) we expect there to be negative correlation between cognitive load and fixations on the speedometer. As an example consider an easy driving task which requires little cognitive resources to be spent. This then leaves plenty of cognitive resources for checking the speedometer. In contrast, a driving task with high visuospatial or central demands allows little "mental space" to concern oneself with the speedometer. This hypothesis is supported by Salvucci and Taatgen (2011), who suggest that drivers perform less control updates (such as checking the speedometer) when engaging in a demanding secondary task.

Alongside these eye-tracking measurements we are interested in how driving performance is influenced by cognitive load. We will examine two measures linked to lateral control of the vehicle and therefore driving performance: lane-keeping and steering wheel reversal (Knappe, Keinath, Bengler, & Meinecke, 2007). Following Savino (2009) we expect a positive correlation between cognitive load and deviation from the center of the lane, as well as a positive correlation between cognitive load and rate of steering wheel reversal.

In order to test our hypotheses a simulated-driving experiment with eye-tracking was conducted in which central and visual demands were manipulated separately. It largely follows the approach of Scheunemann et al. (2019) who studied the interaction between working memory load (WML) and visuospatial demands while driving. Their experiment involved participants driving a car on a highway in a realistic simulation.

WML was manipulated through a slightly modified n-back task. Considered a standard measure of working memory in cognitive neuroscience, a classic n-back task requires participants to decide whether the stimulus they are currently seeing matches the one presented n items ago (Kane, Conway, Miura, & Colflesh, 2007). In the current experiment the task was integrated into the driving process by means of speed regulation, meaning participants were instructed to drive according to the speed sign that occurred n signs ago.

Visuospatial demands were manipulated by contrasting two driving environments: *construction* and *non-construction*. In the non-construction condition participants drove on a regular three-lane highway. In the construction condition the leftmost lane was closed off by a continuous row of pylons and the remaining two lanes were of reduced width, which increases driving difficulty (Liu, Wang, & Fu, 2016).

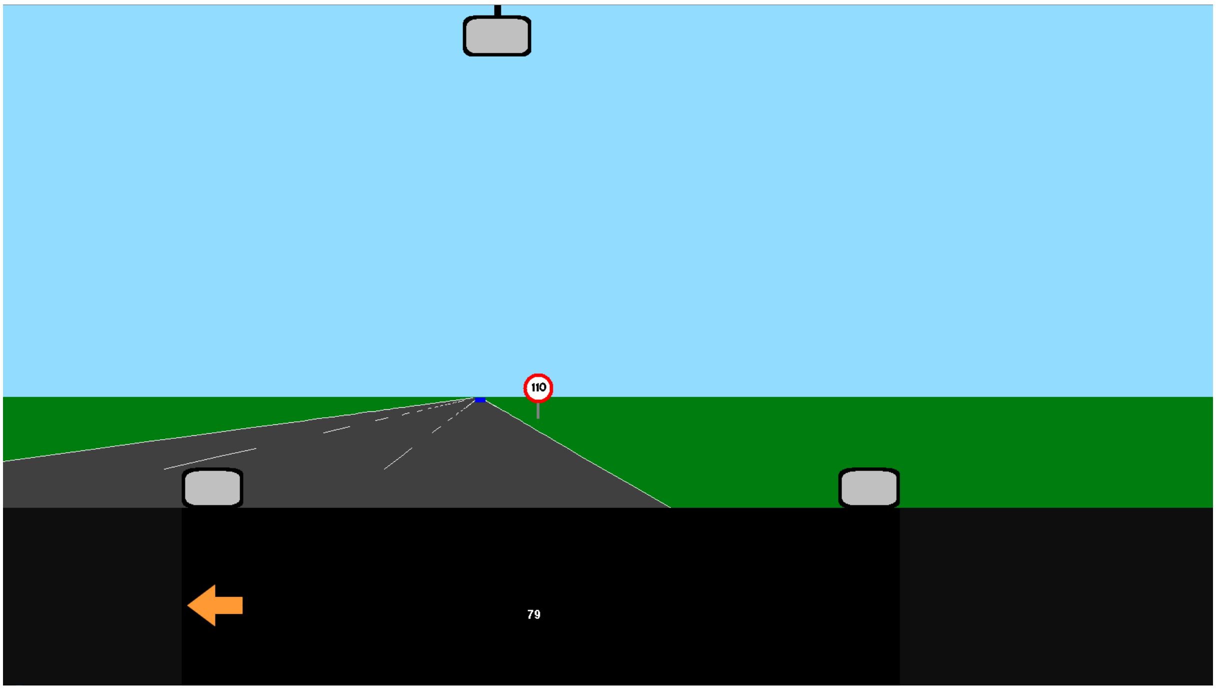


Figure 2.1: The driving simulation for the non-construction condition. The orange arrow on the left of the dashboard is the indicator that blinks three times once the participant presses the indicator. The number at the center of the dashboard shows the current driving speed. At the top and on both sides of the screen are mirrors in which the participant can see the autocar when it is behind them.

2 Methods

2.1 Participants

A total of 38 volunteers (23 male, 12 female, 3 other/undisclosed) aged 20–36 ($M = 23.1 \pm 3.0$) participated in this experiment. They all had a driver's license, on average for 4.5 years ($\pm$ 3.1). All participants signed an informed consent form prior to the experiment and were compensated 12 euros for their participation.

2.2 Materials

Participants interacted with the driving simulation using a steering wheel with indicators and a throttle and brake pedal (Driving Force GT, Logitech, Lausanne, Switzerland). The steering wheel was secured to the table in front of the screen and remained in the same location for all participants. The pedals were placed on the floor such that participants could move it closer or further depending on their level of comfort. An eye-tracking camera (EyeLink Portable Duo, SR Research, Missisauga, Canada), placed between the screen and the steering wheel, was used to continuously record the eye movements and pupil size of participants. The method of tracking that we employed was remote tracking using a target sticker on the participant's forehead. This method was chosen because stabilizing the head using a head rest was not feasible considering the set-up with the steering wheel.

The simulated environment of the experiment consisted of a straight three-lane highway, as shown in Figure 2.1. The features of the environment were minimal. Either side of the road was coloured green, signifying grass. Traffic consisted of a single other car on the highway, referred to as the *autocar* and represented by a blue rectangle. The autocar would stick to traffic rules such as overtaking from the left, staying on the right lane as much as possible, and following the current speed limit.

The bottom of the screen was filled by a black dashboard. At the center of the dashboard the current speed of the car was shown as an integer. When the left or right indicators were pressed, they would appear on the dashboard in the respective sides as orange blinking arrows. The simulation had three rear-view mirrors: one on the top, one on the left, and one on the right. The autocar was visible in the corresponding mirrors depending on the distance from the car.

In the construction condition the leftmost lane is closed off by a row of pylons as shown in Figure 2.2. The lanes were separated by a full yellow line and were narrower than in the non-construction condition.

Speed signs that passed were identical to general speed signs in The Netherlands: black digits enclosed by a red circle.

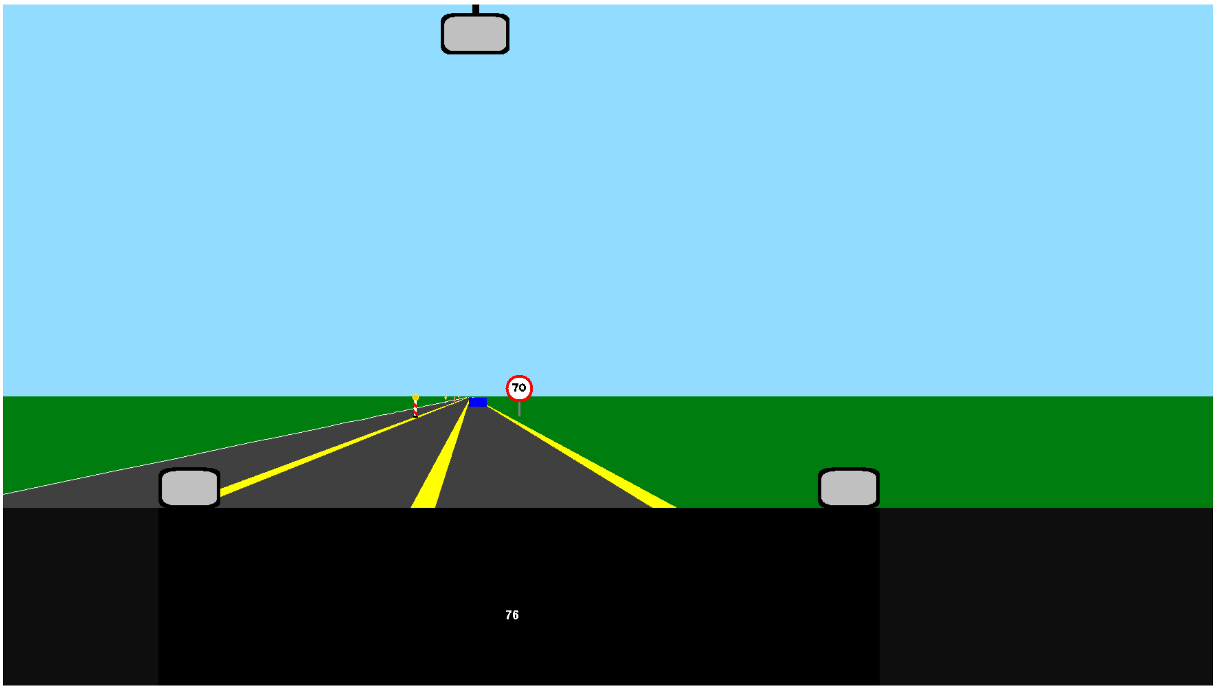


Figure 2.2: The driving simulation for the construction condition. The leftmost lane is closed off by a row of pylons and the remaining lanes are more narrow than in the non-construction condition. The autocar can be seen next to the speed sign.

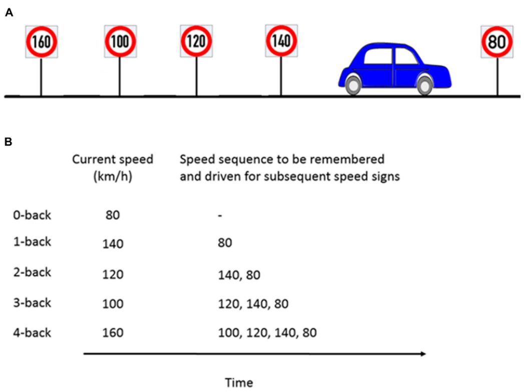


Figure 2.3: Example of n-back experimental paradigm to manipulate working memory load (from Unni et al., 2017).

The n-back task that participants performed during driving is illustrated best by an example from Unni, Ihme, Jipp, and Rieger (2017) as shown in Figure 2.3, which they explain as follows. In this scenario the participant is about to pass the 80 km/h speed sign and the previous four speed signs were as shown in the schematic. For the corresponding n-back task, participants had to memorize the last n speed signs and drive at the nth speed sign which occurred previously. For example, at 1-back, the participant's target speed is the previous sign (140 km/h) and has to keep the current speed sign in memory (80 km/h).

A trial consisted of the participants performing the speed-regulating task for nine speed signs. The speeds shown on the signs were randomized in the range 40–120 km/h in steps of 10 km/h. The signs appeared at intervals of 20 seconds, with the first speed sign being passed at 5 seconds. For n-back tasks with $n \geq 1$ there was a so-called "build-up phase" of n speed signs during which the participant did not need to regulate their speed yet. For example, for $n = 4$, the build-up phase would be the first four speed signs. They would then have to start the speed-regulating task at the fifth speed sign. Because of the build-up phase, the n-back trials differed in number of speed signs shown and therefore in duration. It is important to note here that the build-up phase is excluded from data analysis since it is not considered a part of the n-back task.

2.3 Experimental Procedure

There are 10 unique combinations of n-back level and construction condition. Each of these combinations was performed twice, resulting in a total number of 20 trials. These were divided into two blocks of 10 trials with a short break in between.

The order of the trials was determined pseudorandomly with a few conditions. Firstly, no n-back level could appear twice in a row. Secondly, the construction/non-construction conditions were alternated from trial to trial. Thirdly, the order of the trials in the first block was reversed to form the order of trials in the second block. These constraints on the randomization were incorporated with the aim of avoiding habituation effects for the memory task and the visuospatial demands.

Prior to performing the experiment the participant was given instructions about the driving and the memory task. They then performed a practice round (one 2-back trial with no construction and a total of 5 speed signs) to get accustomed to the task, the simulation and the steering wheel. Next, the eye-tracker was calibrated, which required the participant to follow a target around the computer screen with their eyes. This procedure was repeated twice: once to calibrate and once to validate whether that calibration was accurate. If validation was inaccurate, calibration was repeated.

After calibration, the experiment began. Every trial (excluding the very first one) was preceded by an eye-tracking drift correction. This required the participant to look at a target at the center of the screen. If the measured eye position deviated too far from the position of the target, calibration was performed again. Otherwise the deviation was automatically taken into account with recording of the eye position. Following drift correction, a pop-up message appeared telling the participant which n-back task they were about to perform. The percentage of total trials they had already completed was also shown in the message. The participant could then start the trial by pressing an OK button on the steering wheel. Unlike in the experiment by Scheunemann et al., we did not include warning messages telling participants to change their speed when it was incorrect. We did this to prevent participants guessing the correct speed.

2.4 Data collection

A number of different variables pertaining to driving behavior were recorded at a rate of 200 Hz. The use of the accelerator and brake pedals was recorded as numbers ranging from 0 (not pressed) to 1 (fully pressed). The angle of the steering wheel was recorded as a number ranging from -1 (left) to 1 (right). In order to measure lane centering, the position and orientation of the participant's car were recorded. Finally, the speed of the participant's car was recorded along with the occurring speed signs to calculate n-back task performance.

The eye-tracker recorded a number of raw variables at a rate of 500 Hz, two of which are relevant for the current study. Eye positions were measured in x and y coordinates relative to the PC monitor (1920×1080 px). Pupil size was measured in terms of diameter in arbitrary units. The eye-tracker recorded only one eye (specifically the left) as this is most common in eye-tracking experiments (Hutton, 2019).

2.5 Data analysis

All analyses were conducted using the R programming language (R Core Team, 2020).

The raw eye-tracking data were sorted into fixations, saccades and blinks using the `eyelinker` R package (Barthelme, 2021). Only the fixations were used for data analysis as these are the most reliable measurements of both pupil size and fixation location.

To properly compare pupil size within and between participants, baseline correction is required. According to Mathôt, Fabius, Van Heusden, and Van der Stigchel (2018) baseline correction increases statistical power by accounting for random fluctuations in pupil size over the course of an experiment. To this end, the baseline pupil size is recalculated for each new trial. As a baseline period we chose the time period between the start of the trial and the appearance of the first speed sign. The mean pupil size during this 5 second interval was used to correct the pupil sizes of the trial. The specific method of baseline correction that we used is subtractive baseline correction ($\textit{corrected pupil size} = \textit{pupil size} - \textit{baseline}$) as Mathôt et al. (2018) prefer it over divisive baseline correction ($\textit{corrected pupil size} = \textit{pupil size}/\textit{baseline}$).

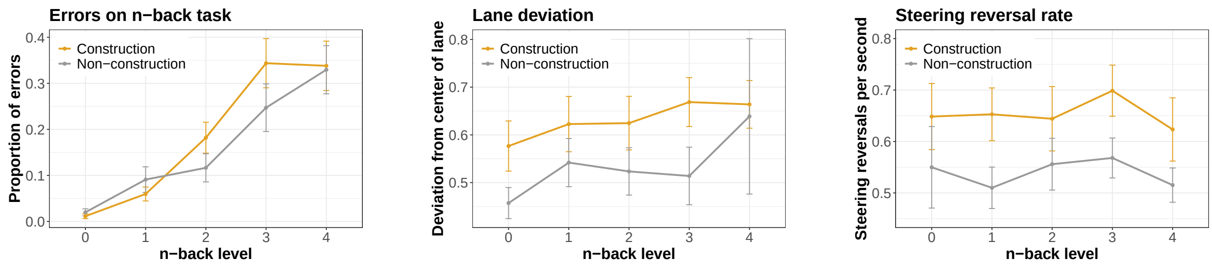
In order to analyze fixations on the speedometer it must be defined as an area of interest (AOI). The bounds of this AOI could not be universally defined since the measurement of eye-positions shifted between and within participants. For this reason we manually determined the borders of the AOI for each participant; in other words, we determined what "counts as" a fixation on the speedometer. Fixations on the speedometer will be expressed as a percentage of the total number of fixations during that trial.

We will focus on three measures relating to the two variables of interest. Pupil size will be examined both between and within trials. These two temporal contexts will provide a detailed image of how a participant's pupil size changes over time. Fixations on the speedometer will be examined between trials. In order to test the significance of the results we will use a two-way ANOVA with repeated measures, with n-back level and construction/non-construction as independent variables.

3 Results

3.1 Participants

From the 38 individuals that participated in this experiment 16 were excluded from data analysis altogether. 8 participants were excluded because their driving behavior was not indicative of an



(a) Errors on the n-back task (N = 22). From De Mooij (2021).

(b) Lane deviation (N = 22). From Kelapanda (2021).

(c) Steering reversal rate (N = 7). From Kelapanda (2021).

Figure 3.1: Measures of driving performance. Bars represent standard error.

actual attempt to perform the task. 8 additional participants were excluded due to an error in the experiment, leading to the trials being too short. This altered the task considerably and therefore we cannot compare the behavior of these participants to others. Thus, task error (see De Mooij, 2021) and lane deviation (see Kelapanda, 2021) were determined for 22 participants.

For eye-tracking analysis specifically, 6 more participants were excluded as their eye-tracking data were incomplete. This leaves us with 16 participants for eye-tracking analysis. Finally, for the analysis of steer reversal rate (see Kelapanda, 2021) 15 participants were excluded because of missing data, leaving 7 participants for analysis.

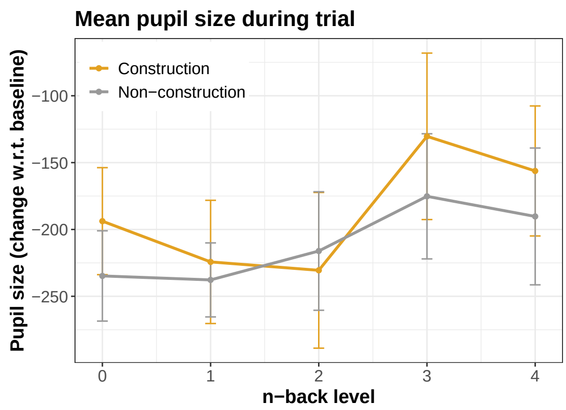


Figure 3.2: Mean pupil size during trial (N = 16).

3.2 Driving performance

Let us first examine performance on the working memory task. Figure 3.1a shows a positive correlation between n-back level and the proportion of errors, confirming that the n-back task indeed gets more difficult with increasing n. There is no effect of the construction condition, nor an interaction between n-back level and construction on the error rate. This suggests that visuospatial demands do not impact performance on the working memory task.

Figure 3.1b shows the average deviation from the center of the lane. While n-back level has no significant influence on lane deviation, there is a significant effect of construction condition. These results indicate a positive correlation between visuospatial demands and lane deviation, and no influence of working memory load.

Figure 3.1c shows the rate of steering reversal. We see an increase in steering reversals in the construction condition compared to the non-construction condition. No significant effect of n-back level is found.

3.3 Pupil size

Figure 3.2 shows the mean pupil size over a trial. There seems to be a correlation between n-back level and pupil size. A two-way ANOVA with repeated measures confirms this effect of working memory load (WML) on pupil size $[F(4, 135) = 3.09,\ p = .018]$. No significant effect of visuospatial demands $[F(1, 135) = 1.88,\ p = .17]$ nor an interaction between WML and visuospatial demands $[F(4, 135) = 0.40,\ p = .81]$ is found.

Figure 3.3 shows how the pupil size of participants changed within a trial. It is immediately noticeable that pupil size for speed sign number $0 - n$ is equal to zero for all n-back levels. This is explained by our definition of the baseline period (the first five seconds of a block) as speed sign number $0 - n$. Hence, the corrected pupil size for this first "speed sign" is $baseline - baseline = 0$.

Looking at the changes in pupil size for $n = 0, 1$ we see a nearly continuous decrease in pupil size over the trial, indicating a low cognitive load. In contrast, $n = 3, 4$ show a larger pupil size, suggesting higher cognitive load.

3.4 Fixations on speedometer

Figure 3.4 shows the number of fixations on the speedometer as a percentage of the total number of fixations for a trial. Like this figure suggests, there is a significant negative correlation between n-back

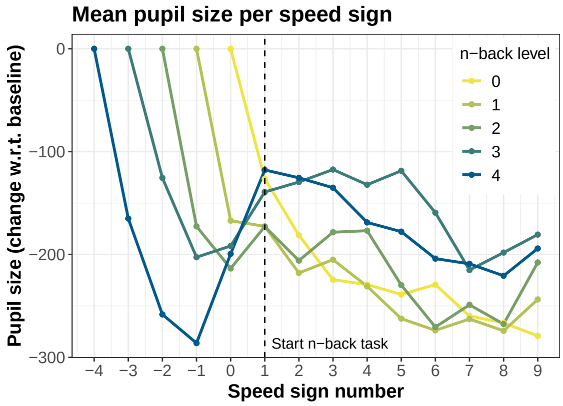


Figure 3.3: Mean pupil size over the period between the appearance of two speed signs (N = 16). The dashed vertical line indicates the end of the build-up phase, i.e. the start of the speed regulating task.

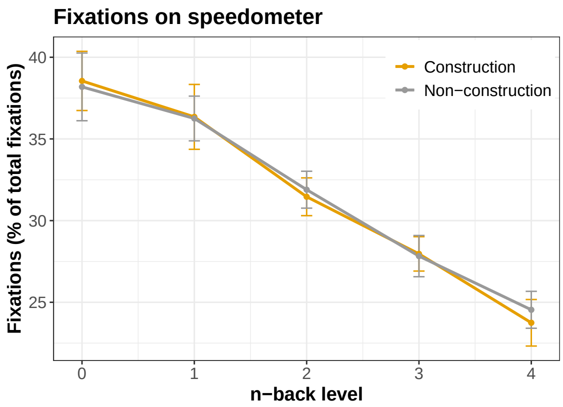


Figure 3.4: Number of fixations on the speedometer as a percentage of the total number of fixations for that trial (N = 16); bars represent standard error.

level and fixations on the speedometer $[F(4, 135) = 51.55,\ p < .001]$. There is no effect of construction $[F(1, 135) = 0.03,\ p = 0.86]$ nor an interaction between n-back level and construction $[F(4, 135) = 0.085,\ p = 0.99]$.

4 Discussion

In this study we sought to answer three questions related to cognitive load while driving by means of an eye-tracking experiment. Firstly, can the current level of cognitive load be predicted by pupil size? Secondly, does the frequency of fixations on the speedometer correlate with the current level of cognitive load? And thirdly, what is the influence of cognitive load on driving performance? Below you will find our conclusions based on the results of the experiment.

First consider the effect of working memory load (WML) on pupil size. Between trials we found an effect of WML on pupil size. However, the same cannot be said for visuospatial demands. Our results therefore suggest that pupil size is a predictor for WML, but not for visuospatial demands.

Interestingly, Figure 3.3 shows a decline in pupil size for $n = 4$ after the start of the n-back task. We suggest the following explanation. While participants focus their attention on the task at first (causing their pupil to dilate), they quickly abandon the task because of its difficulty, resulting in a contraction of the pupil. This explanation is supported by Granholm, Asarnow, Sarkin, and Dykes (1996) who found that pupil size declines when an individual is experiencing an overload of working memory.

Next, results showed that the number of fixations on the speedometer decreased by WML. We conclude that as WML increases, fewer cognitive resources are available for speed checking. This is in line with findings on the effect of secondary tasks on control updates during driving, as described by Salvucci and Taatgen (2011). In this context we again see no influence of visuospatial demands, suggesting that only WML affects speed-keeping efforts.

Finally, our findings on lane deviation and steering reversals can be summarized as a negative correlation between visuospatial demands and driving performance.

What are then the practical implications of these results? We have established that pupillometry can be used to assess working memory load (WML) during driving, yet reveals little about visuospatial demands on the driver. It therefore does not suffice as a robust measure of cognitive load. Instead, it could be used in combination with a measure of visuospatial demands. Further research is required to find this measure and validate its use in combination with pupillometry while driving.

Moreover, the confirmed correlation between WML and speed-keeping efforts highlights speed-keeping as a topic of interest in the field of adaptive automation. It is important to note that in this experiment, speed-keeping and the n-back task were closely related. Our conclusion can therefore not be extended immediately to "regular" speed-keeping. Rather, it should be evaluated by an experiment in which the memory task and speed-keeping are separated.

Lastly, the correlation between visuospatial demands and both lane deviation and steering reversals suggests that these two measures are of interest to adaptive automation as well.

There are some limitations to this study. Firstly, the driving set-up consisted of only a computer screen and a steering wheel with pedals as used in video games, making it a low-fidelity simulation

(Knappe et al., 2007). Secondly, the simulation itself was quite simplistic with concurrent traffic being limited to one car. These two factors decrease the statistical power of our results, and future research should seek to employ realistic, high-fidelity simulations.

Thirdly, the modified n-back task has not been confirmed to be a measure of working memory load like the classic n-back has. In the classic n-back task an individual must compare the current stimulus to the stimulus that occurred n stimuli ago. This requires them to first encode the current stimulus, then retrieve the previous stimulus from working memory and finally compare both items. In contrast, our n-back task did not require comparison between stimuli. As a result, participants could first retrieve the previous stimulus and afterwards encode the current stimulus. The speed regulation task might therefore place less demands on working memory than the classic n-back task. At the same time, the interstimulus interval (ISI) of the current experiment could place *more* demands on working memory. Whereas other n-back tasks have an ISI of 1.5 s (Juvina & Taatgen, 2007), 2.5 s (Jaeggi, Buschkuehl, Perrig, & Meier, 2010; Miller, Price, Okun, Montijo, & Bowers, 2009) or 3.5 s at most (Perlstein, Dixit, Carter, Noll, & Cohen, 2003), our task has an ISI of 20 s. Since the modified task is substantially different from a classic n-back task, further research should focus on its validity as a manipulation of working memory load.

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