Cognitive Load and Anxiety as Predictors of Driving Performance:

Insights into Physiological and Psychological Factors

By

Katharina Park

2077389

Cognitive Neuroscience

Bachelor's thesis

Date of Submission: 30/06/2024

Name of the Supervisor: Dr. Gijs Holleman

Second Reader: Nadya Ali, MSc

University College Tilburg
Tilburg School of Humanities and Digital Sciences
Tilburg University

Abstract

Road accidents are a common occurrence, and driving performance is affected by many factors. Therefore, investigating which variables can influence decision-making and performance during driving is crucial for reducing the number of traffic accidents. The aim of the current study was to explore if driving performance can be predicted by anxiety levels and through pupil dilation change, which is a measure of cognitive load. Participant's anxiety levels were assessed with a self-reported questionnaire and pupil dilation changes were recorded with an eye-tracker while participants engaged in a continuous driving task. A mixed-effects model and correlational analyses were utilized to assess whether anxiety levels and pupil dilations changes influenced driving performance and if they were correlated. Squared Pupil Dilation change, a measure of cognitive load, was found to be a significant predictor of driving performance and the association was negative. No association between anxiety levels and driving performance, and anxiety levels and pupil dilation change were found. The study results provide insights into the physiological and psychological underpinnings of driving behavior and can contribute to the development of advanced driver-assistance systems and interventions for improving traffic safety. Future research would benefit from larger and more diverse samples, using VR and including other physiological measures.

Introduction

Road injuries and traffic accidents are ranked as the tenth leading cause of death worldwide (Mathers et al., 2017). Driving is a common yet intricate activity, during which individuals need to perform various tasks simultaneously: steer, brake, maintain awareness of surrounding traffic, adhere to speed limits and road signs, and successfully navigate to their destination. As driving involves information storage (e.g. remembering traffic signs) and attentional control, working memory has an important role in the realm of driver information processing (Zhang et al., 2023). Additionally, working memory is a crucial element of cognition and therefore cognitive load, which refers to the strain imposed on working memory while performing a specific task (I-Jung & Chi-Cheng, 2009; Wang et al., 2023). This cognitive load also plays a crucial role in driving endeavors. Hence, the aim of this thesis project was to investigate whether changes in pupil dilation (an indicator of cognitive load) along with anxiety traits that impact working memory capacity can predict the performance in a continuous driving task. To begin, the topic will be introduced by discussing: the importance of working memory in driving behavior, the dual-systems approach to information processing and cognitive load theory, and the impact of anxiety traits on working memory. Following this, a comprehensive review of the existing literature is provided, which discusses the relevance of cognitive load and anxiety for driving performance and behavior, and the role of pupil dilation as an indicator of cognitive load. Next, an overview of the current study is presented, followed by a detailed explanation of the methods used. Finally, I will discuss the results and their implications.

The importance of working memory for driving behavior

Working memory (WM) holds a limited amount of information in a readily accessible format, aiding tasks such as planning, understanding, logical thinking, and problem-solving

(Cowan, 2013). It can be divided into three parts: verbal WM, the visual-spatial WM, and the central executive, which involves the attentional control system (Chai et al., 2018). During the act of driving, drivers need to manage certain levels of physical and cognitive demands (Wang et al., 2023). Various distractions, including engaging in secondary tasks, roadside distractions, and conversation, can contribute to a driver's cognitive load (Lansdown et al., 2004). An elevated cognitive load has the potential to overwhelm an individual, which could lead to catastrophic accidents (Wang et al., 2023). Furthermore, past studies have revealed that both excessively high levels of cognitive load (referred to as "cognitive overload") and excessively low levels of cognitive load (referred to as "cognitive underload") can result in poor performance, as cognitive overload can negatively affect working memory performance, while cognitive underload can lead to a lack of motivation and boredom (Vanneste et al., 2020). Therefore, an appropriate level of cognitive load ensures the optimal performance (Vanneste et al., 2020).

A dual-system's approach to information processing and cognitive load theory

The dual-system theory by Kahneman provides insight into how cognitive load can impact behavior (Deck & Jahedi, 2015; Kahneman, 2011). The framework proposes that individuals have two different systems: an “intuitive” system and a “reasoning” system. When one needs to make a decision, the intuitive system quickly makes a judgment, which then the reasoning system overrides at a cost. When there are enough cognitive resources, the reasoning system is able to suppress impulsive or undesirable behaviors. However, when under high cognitive load, the demand on the reasoning system is increased and its ability to regulate decision-making decreases, leading to less reasoned behavior. For example, in their research on the effects of cognitive load on economic decision-making, Cary Deck and Salar

Jahedi (2015) found that higher cognitive load led to more risk-averse behavior and impatience.

Impact of Anxiety on Working Memory & Cognitive Load

Another factor that can influence the amount of cognitive load is anxiety (Vytal et al., 2013). As anxiety consumes resources assigned to goal-directed behaviors such as spatial attention and executive function, working memory capacity (WMC) to perform these tasks decreases and therefore various types of performances decline (Moran, 2016; Vytal et al., 2013). The APA dictionary of psychology defines anxiety as: “an emotion characterized by apprehension and somatic symptoms of tension in which an individual anticipates impending danger, catastrophe, or misfortune” (APA, 2018). Anxiety can be dissected into two primary dimensions: worry/apprehension and arousal/emotionality (Moran, 2016). "Worry" consists of verbal rumination about potential negative future outcomes and is commonly associated with generalized anxiety disorder (Moran, 2016). In contrast, "arousal" refers to physiological hyperarousal and bodily tension, characterized by symptoms like dizziness, increased heart rate, sweaty palms, and hypervigilance, typically observed in stressful situations and panic (Moran, 2016). Anxiety disorders are the most prevalent mental disorders affecting anywhere between 3.8-25% of people (Delpino et al., 2022; Remes et al., 2016). They trigger mechanisms focused on avoiding harm, affecting various cognitive processes including perception, attention, learning, and executive function. This can be adaptive or maladaptive depending on the situation, impacting functions like working memory while leaving others, such as planning, unaffected (Robinson et al., 2013).

Cognitive deficits are an acknowledged part of anxiety (Moran, 2016). When anxiety consumes resources allocated to goal-directed behaviors like spatial attention and executive function, different types of performance tend to decrease (Vytal et al., 2013). Anxiety indicators have reliably been associated with increased distraction from irrelevant stimuli during search tasks, reduced proficiency in reading comprehension, and mathematical problem-solving, as well as lower scores on standardized tests assessing intelligence and overall aptitude/achievement (Moran, 2016).

The majority of theories suggest that the connection between anxiety and working memory capacity (WMC) arises from interference or competition between anxiety-related and task-related processes (Moran, 2016). Because worry entails verbal contemplation, it is commonly believed to disrupt the retention of verbal information. Several theories posit that worry functions as a form of dual-tasking, impeding cognitive task performance. For instance, Sarason proposed that anxiety involves task-irrelevant thoughts and a tendency towards self-preoccupation (Sarason, 1988). These worrying thoughts were hypothesized to diminish the attention available for task execution (Moran, 2016).

According to processing efficiency theory (PET) and attentional control theory (ACT), worry is believed to influence attentional processes, aligning with Sarason's (1988) perspective. However, ACT expands on this notion by proposing that anxiety also impacts specific executive functions, including inhibition. (Moran, 2016)

Notably, studies indicate that anxiety-related deficits in verbal working memory (WM) are influenced by task complexity, highlighting the significance of cognitive load in the interplay between anxiety and cognition. Anxiety affects both verbal and spatial processes, evidenced by correlations between anxiety levels and performance decrements. However, the impact on spatial working memory remains consistent regardless of cognitive load. (Vytal et al., 2013)

More recent models suggest that anxiety dimensions (worry versus arousal), along with different types of working memory (verbal versus visual), and task difficulty interact. Vytal and colleagues propose that the dimensions of anxiety can disrupt specific mental functions. They suggest that arousal affects spatial thinking, while worry affects verbal thinking. They also note that worrying thoughts can be controlled better by conscious effort than arousal. They further suggest that worry mainly affects verbal thinking when tasks are easy, but under tough conditions, other mental functions become more important, leading anxious individuals to find ways to improve their performance. (Moran, 2016)

The results of the meta-analysis and narrative review by Moran (2016), found that the severity of symptoms significantly influenced the association between anxiety symptoms and working memory capacity (WMC). While effect sizes were significant in both clinical (subjects exhibiting clinically significant symptoms) and subclinical samples (subjects with mild and minimal symptoms), those in clinical populations were notably larger.

Additionally, he found that both worry and arousal were predictive of performance on both phonological and spatial tasks. This observation appears to challenge the domain-specific predictions of existing theories. However, it is important to note that while worry and arousal typically represent separate dimensions, they are not entirely uncorrelated. (Moran, 2016)

Cognitive load and Anxiety and their relevance for driving performance/behavior

Understanding the connection between cognitive load, anxiety, and driving behavior is crucial, as it could significantly influence performance on the road. Both excessive and insufficient cognitive load have the potential to cause accidents by impairing the driver's ability. Thus, investigating this relationship is essential for preventing traffic collisions (Vanneste et al., 2020; Wang et al., 2023). Moreover, given that anxiety markers have previously been linked to reduced performance and anxious characteristics are thought to diminish working memory capacity, possibly resulting in increased cognitive load, it is important to further investigate the indirect effect (mediated by cognitive load) and direct effect of anxiety on driving.

Pupil Dilation as a Measure of cognitive load

The relationship between cognitive load and driving performance can be studied by looking at pupil dilation. As in 1964, Hess and Polt established a relationship between pupil dilation and cognitive load, with pupil diameter increasing with task difficulty. Building on their research in 1966, Kahneman and Beatty proposed that changes in pupil size serve as a highly reliable indicator of the current cognitive load experienced by an individual during mental tasks (Kahneman & Beatty, 1966). The findings by Szulewski et al. (2016) have further proved the validity of using physiological metrics (e.g. pupillometry) to measure cognitive load.

In the current experimental paradigm, pupillometry is a well-studied physiological method to measure cognitive load. It works by tracking the changes in participants' pupil diameter while they engage in cognitive and behavioral tasks that require working memory. Pupil size change is considered to reflect information-processing and the utilization of cognitive resources. (Szulewski et al., 2016) According to a review by Van der Wel & van Steenbergen (2018), many studies indicate that pupil dilation increases with task demands. Pupil diameter increases with tasks that require higher cognitive load, due to the activation of the central autonomic nervous system (Szulewski et al., 2016). The autonomic nervous system (ANS) is responsible for unconscious activities, including breathing and digestion (Kolb et al., 2019). ANS can be divided into two divisions: Sympathetic and Parasympathetic. While the sympathetic nervous system (fight or flight) leads to pupil dilation, the parasympathetic (rest and digest) leads to constriction (Kolb et al., 2019). As high cognitive load leads to pupillary diameter expansion due to ANS activity, pupillometry is considered to be a good estimate for the level of cognitive load experienced by the participant at a particular moment in time (Szulewski et al., 2016).

Present study

The present study examines the potential of pupil dilation as a predictor of driving performance. Furthermore, it explores whether anxiety traits/levels increase average pupil dilation and negatively impact performance in a continuous driving task. No previous research has been done that relates the pupil size dilation to decision-making during driving behavior and driving performance. Additionally, the study will add to the theoretical knowledge by investigating the relationship between generalized anxiety and driving performance. The following research questions will be addressed: 1) Can pupil dilation as a measure of cognitive load predict the performance on a continuous driving task? 2) How does anxiety influence pupil dilation as a measure of cognitive load and predict performance on a continuous driving task?

The participants engaged in a continuous driving task, during which changes in pupil size were measured. Each time a participant passed a car, their performance was evaluated with a positive or negative outcome score. Additionally, data on the participants' anxiety levels were collected prior to the experiment.

As cognitive load plays an important role in driving and as high and low levels of cognitive load can potentially lead to accidents due to underperformance, it is important to gain insights into the relation between cognitive load and driving behavior to possibly avoid traffic collisions (Vanneste et al., 2020; Wang et al., 2023). This can be done by measuring pupil dilation (higher load results in more pupil dilation) (Szulewski et al., 2016; van der Wel & van Steenbergen, 2018). Therefore, the following hypotheses will be tested: 1) Moderate pupil dilation change, defined as those changes that fall within the interquartile range (IQR) of the data distribution, during a trial will lead to more positive outcomes on the driving task (which serves as a measure of driving performance), while a bigger change in pupil dilation will result in a negative outcome on the driving task.

Additionally, since anxiety indicators have been previously associated with lower achievements and anxious traits are believed to decrease working memory capacity, and therefore, potentially leading to more cognitive load, the following is hypothesized: 2) Anxiety traits negatively influence a person’s driving performance, as indicated by a negative correlation between anxiety scores and the success rate 3) Higher levels of anxiety, as measured by self-report scale GAD-7, will be associated with a larger average pupil dilation, indicating greater cognitive load, during the continuous driving task.

Methods

Participants

The number of tested participants was 41, and the number of included participants was 27 (5 men, 22 women). The 14 participants were excluded from the study due to missing data (e.g., driving experience). All the participants were aged 18 or older. The average age for a participant was 21.78. The criteria for the participants were to be proficient in Dutch and/or English and possess normal or corrected-to-normal vision and hearing. Most of the participants were students at Tilburg University, recruited through SonaSystems, an online recruitment tool. The students received credits for their participation in the study. The participants gave informed consent to participate in this research and were aware of being able to withdraw at any moment. The study was approved by the ethical committee.

Study design and methodology

The study consisted of two parts, during the first (online) part, participants filled in the Generalized Anxiety Disorder scale (GAD-7) to assess their anxiety levels. The second part was performed in the lab and included a driving simulation task. The participants' pupil diameter changes (and the baseline) were measured during the driving task with the Tobii Pro Spectrum video-remote eye-tracking system, running at 600 Hz.

Materials

Anxiety Questionnaire

The GAD-7 (the Generalized Anxiety Disorder) scale was used to assess anxiety levels. GAD-7 is designed to assess the extent to which someone has experienced anxiety-related symptoms in the past two weeks. It has 7-items, with a 4-option answer scale. The answer options are: “not at all”, “several days”, “more than half of the days”, “nearly every day”. The scores 0, 1, 2, 3 are assigned to the response categories, respectively, and the scores are added up. The scores ranged from 0 to 21, with the following interpretations: 0–4: minimal anxiety, 5–9: mild anxiety, 10–14: moderate anxiety, 15–21: severe anxiety. (Spitzer et al., 1999)

Gaming & Driving Questionnaire

The driving questionnaire consisted of three questions: 1) How many years of driving experience do you have (i.e., years in which you've driven at least once)? 2) On average, over the past five years, how frequently have you driven in the city? 3) On average, over the past five years, how frequently have you driven on a highway (i.e. speed limit at least 100 kph, distance at least 30 km)? The first question had the following answer options: “n/a”, “less than 5 years”, and “5-10 years” and were scored respectively 0, 1, 2 points. The second and third questions had the following answer options: “one day or less per week”, “one to three days per week", "four to five days per week", and "six to seven times per week" and were scored respectively 1, 2, 3, 4 points. All the points were added together to get a driving score.

The gaming questionnaire included two questions. The first question was: what best describes your previous experience (more than five years ago) with action video games (first-person shooter, racing, fighting, etc.)? and had the answer options: "I have virtually never played them", "I used to play them occasionally (less than 3 times per week)", and "I used to play them a lot (more than 3 times per week)". The first answer had a score of zero, the second a score of one, and the third a score of two. The second question was: what best describes your current experience (within five years) of action video games? With the following answer options: "I virtually never play them (score of zero)", "I play them occasionally (less than 3 times per week)" (score of one), "I play them a lot (more than 3 times per week)" (score of two). All the scores were added together to get a gaming score.

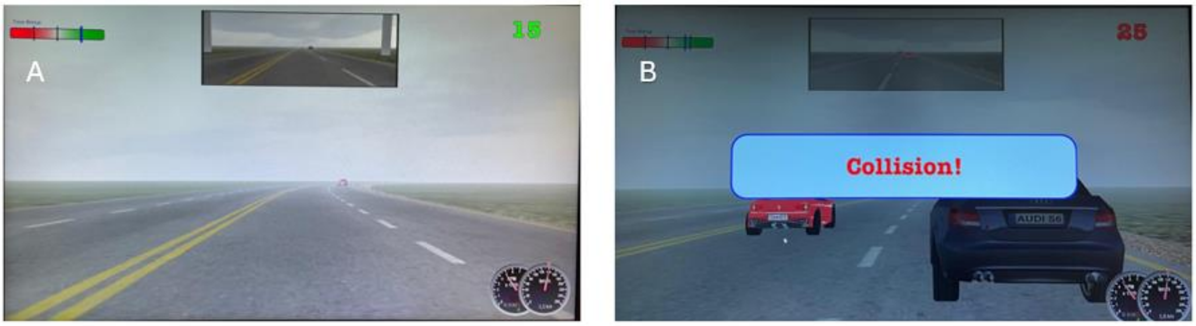
Continuous driving task

The driving task had 16 rounds, lasting around 40 minutes in total. Each round lasted between 2 to 3 minutes, depending on the participant's speed. The participants used a 12-button controller to change the speed of the car from 0-140 kmph (up/down arrows), to change lanes (left/right arrow buttons), to brake (B-button), to start or pause the simulation (start button), and to answer questions about road signs (left/right arrow button). See Figure 2 for a photo of the controller.

During a "round", the participant had to navigate a simulated highway loop and avoid crashing into other vehicles. The participant was instructed to complete the round as quickly as possible, while avoiding collisions. When the participant got into a car accident, the round restarted, and they lost points (Figure 1B). In contrast, driving safely yielded participants points (e.g., safe overtaking). Participants received instant feedback via either green (positive) or red (negative) numbers displayed on the upper left corner of the screen (see Figure 1A). For the analysis, a binary outcome measure was used, which reflected whether during a trial, defined as a passing event, the participant got negative or positive points. Positive points were achieved by overtaking a car in a safe manner, while negative points were received when there was an unsafe passing or a collision.

Figure 1

Photos from the Driving Simulation



Note. Photos taken during the driving simulation. (A) Upper left- time-bonus bar, upper right- gained points, lower left corner- speedometer and tachometer. (B) Photo from driving simulation after a collision, leading to negative points.

Memory sub-task. During the task, overhead road signs were encountered (two times). The road signs contained place names, which were randomly generated from a list. The sign contained four place names and arrows pointing to their direction. Participants were instructed to remember the location of each place name, and at the end of each round, they were asked to recall the location of one of the eight place names. In the current study the data collected during the memory sub-task will not be used for further analysis.

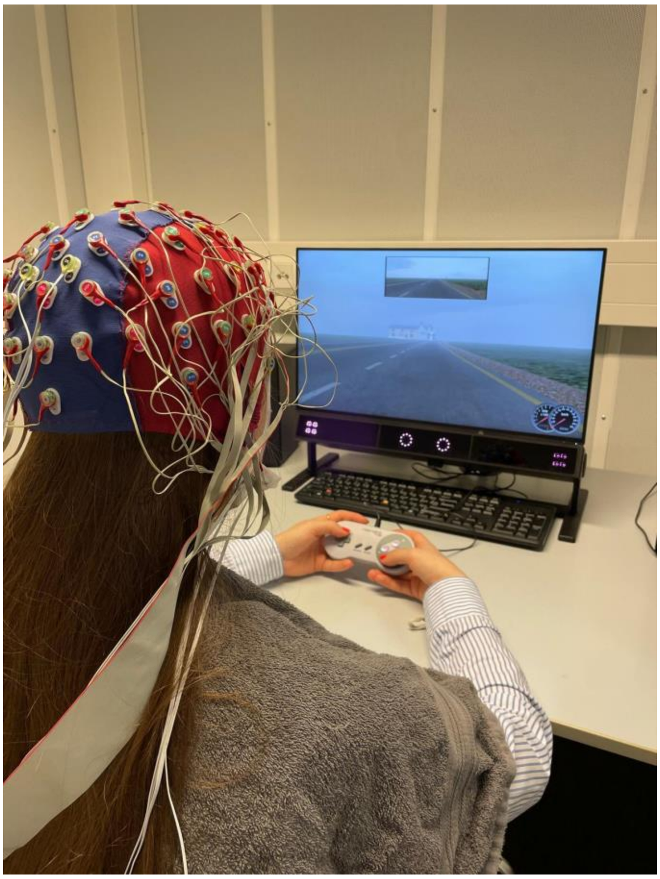
Experimental Set-up and the Eye Tracking System

The experiment took place in a soundproof room, with white walls. The room was equipped with a camera and a microphone, so the participant would be able to communicate with the researcher (and the researcher with the participant) if needed. The participant was sitting down on a chair, and the task was completed on a computer screen with the Tobii pro eye tracker underneath it to record pupil activity (Figure 2).

The Tobii Pro Eye tracking system was used to measure changes in pupil dilation. The eye tracking mode was set to human, and the sampling rate was set to 600 Hz. Before the start of the driving task, the eye tracker was calibrated. The calibration was accepted when the error was reasonable (1-2mm). If the error was bigger, and the calibration did not improve after 3 tries, it was accepted and noted down.

Figure 2

Participant in the experiment room, before the start of the experiment.



Note. The participant is seated in front of a computer screen with the Tobii Pro Spectrum right beneath it, wearing an EEG cap and holding the controller.

Procedure

All participants were invited to the Cognitive Neuropsychology lab at Tilburg University. After the participant entered the lab, each participant was given an overview of the study and asked to sign a consent form. As this study is a part of a bigger research project that also measures EEG activity, the EEG was set up by two experimenters. Next, the participant was guided to the experiment room. First, the eye tracker was calibrated, and then necessary adjustments (e.g., adding conductive gel) were made to ensure a good EEG signal.

The participants were instructed on how to use the controller, about the goal of the game (to go as quickly as possible, while avoiding collisions), to stay in the right lane unless overtaking, and to pay attention to the road signs. Additionally, they were informed that there will be 16 rounds, lasting around 40 minutes in total, that they can pause at any point (by clicking start), and they can withdraw at any point without giving a reason.

Preprocessing

The raw data of the continuous driving game contained state data (e.g., time, position, etc.) for all events, including button presses, collisions, start/end times of traffic events, rounds and the simulation. The raw eye-tracking data contained: 1) Gaze data, including pupil diameter, and 2) event data. The data was converted into CSV tables for specific events and synchronized with the eye-tracking data using event triggers. Epochs were defined as either baseline or passing events. Gaps in the data were identified and removed from the time-series. Eyeblink events were identified using an automated script and interpolated linearly. Average pupil diameters over epochs were calculated. The average pupil diameters per epoch were then Z-scored. The passing epochs were subdivided into positive and negative outcome categories.

For the mixed-effect logistics model that tested the first hypothesis, a mean pupil change for each passing event was determined by subtracting the baseline mean pupil measurement (taken before the passing epoch) from the mean pupil measurement during the passing epoch. The Squared Pupil Change was then calculated by squaring the Mean Pupil Change. The anxiety scores, gaming experience, and driving experience scores were coded and matched to the participants. This resulted in 1029 trials (defined as a passing event), together with 1029 pupil change measurements and outcomes (positive/negative).

Additionally, for the second and third hypotheses, the average pupil size change per participant was calculated. Furthermore, the success rate of participants was determined by dividing the number of successful (positive outcome) trials by the total number of trials per participant.

Statistical Analysis

To answer the first research question: can pupil dilation as a measure of cognitive load predict the performance on a continuous driving task? And to test the hypothesis that moderate pupil dilation change, defined as those changes that fall within the interquartile range (IQR) of the data distribution, during a trial will lead to more positive outcomes on the driving task (which serves as a measure of driving performance), while a bigger change in pupil dilation will result in a negative outcome on the driving task, a mixed-effects logistics regression model was used. The dependent variable was a binary outcome variable (either positive or negative). The independent variables were mean pupil change, the square of mean pupil change (to account for the expected quadratic relationship), driving experience, and gaming experience. The model can be described by the following equation: log (P (positive outcome)/ (1−P (positive outcome))) = b0 + b1(pupil change) + b2(pupil change)^2 + b3(Driving Experience) + b4(Gaming Experience). The mixed-effects model accounted for the repeated measures within participants by including random intercepts for each participant.

For the second research question: how does anxiety influence pupil dilation as a measure of cognitive load and predict performance on a continuous driving task? correlation analyses were done. The first analysis tested the second hypothesis: anxiety traits negatively influence a person's driving performance, as indicated by a negative correlation between anxiety scores and the success rate, by looking at the association between anxiety scores, as measured by the GAD-7 scale and success rate. The second analysis tested the third hypothesis that higher levels of anxiety, as measured by the self-report scale GAD-7, will be associated with a larger average pupil dilation, indicating greater cognitive load, during the continuous driving task, by looking at the correlation between average pupil dilations per participant and their anxiety scores.

Results: Mixed-Effects Logistic Regression

The Mixed-Effects analysis was performed to test the hypothesis that moderate changes in pupil dilation, within the interquartile range (IQR) of the data distribution, are associated with better driving performance, while larger changes in pupil dilation lead to worse driving performance. First, the descriptive statistics of the variables are presented, followed by the results of the clustering analysis, and finally the findings are reported.

Measures

41 participants took part in this study. However, due to missing data 27 participants were included in the analysis resulting in 1029 trials in total. The number of trials per participant ranged from 15 to 64 trials. A “trial” was defined as a passing event, where the

participant changed lanes to overtake another car. This could result in either a negative or positive outcome, reflecting either a successful or an unsuccessful overtaking. Successful meaning a car was passed in a safe manner and unsuccessful meaning that there was a car crash, or the vehicles were dangerously close to each-other.

The trials lasted from 715ms to 49430ms and had a mean of 11079.52ms. The standard deviation was 7440.48, meaning that 68.2% were between 3639.04 and 18519.10 ms. See appendix Table A1.

The dependent variable was binary representing either a positive or a negative outcome of the trial. Positive outcome was coded as 1, while a negative outcome was coded as 0. 37.5 % or 386 trials out of 1029 had a negative outcome and 62.5% or 643 trials (out of 1029) had a positive outcome (appendix Table A2).

The predictor variables for the trial outcomes were Mean Pupil Change (MPC) and Squared Pupil Change (SMPC). Mean Pupil Change was calculated by subtracting the baseline mean pupil measure before the trial from the mean pupil measure during the trial. Squared PC was calculated by squaring Mean Pupil Change. Mean Pupil Change as well as Squared PC were Z-scored.

Mean Pupil Change during the 1029 trials ranged from -3.32 to 3.76 with a mean of .43 and a standard deviation of .94. Squared PC ranged from .00 to 14.15 with a mean of .43 and a SD of 1.75. Consult to Figure 3 for the distribution of the predictor variables and Table 1 for their descriptive statistics.

The confounders for the trial outcomes were Score (Gaming) and Score (Driving). For gaming the scores ranged from zero to four. Four meaning that the participants used to and still play a lot of action video games and zero that they have no gaming experience. The mean was 1.02 and the SD was 1.39. For Driving the scores ranged from zero to nine with a mean of 3.88 and SD of 2.8. With zero indicating no driving experience. The descriptives for the confounders can be found in Table 1 and their distribution at Figure 4.

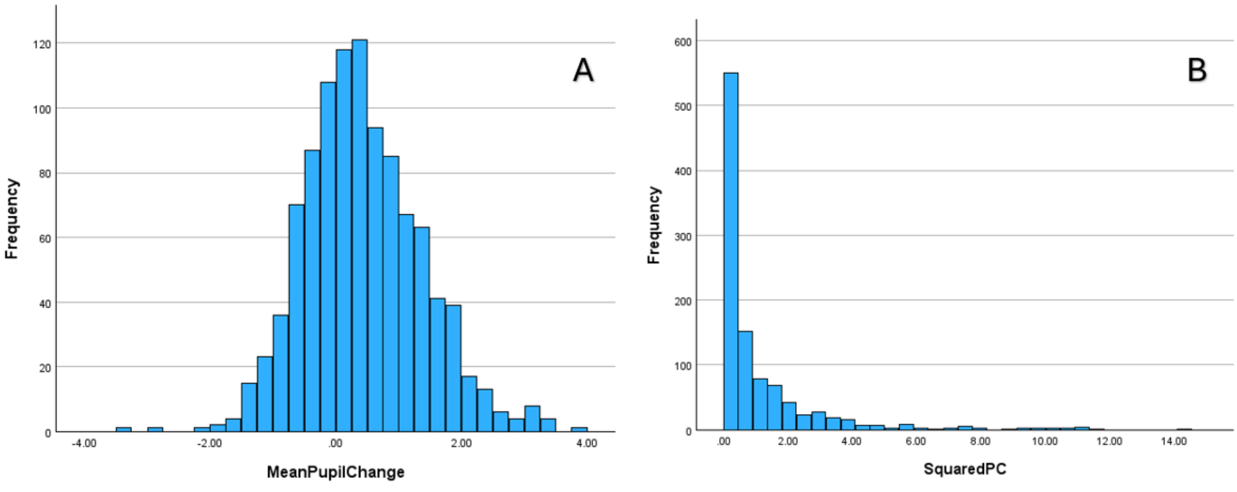
Table 1

Descriptives for Independent Variables

		N	Minimum	Maximum	Mean	Std. Deviation
Predictors	MPC	1029	-3.32	3.76	.43	.94
	SMPC	1029	.00	14.15	1.06	1.75
Covariates	Gaming	1029	0	4	1.02	1.39
	Driving	1029	0	9	3.9	2.84

Figure 3

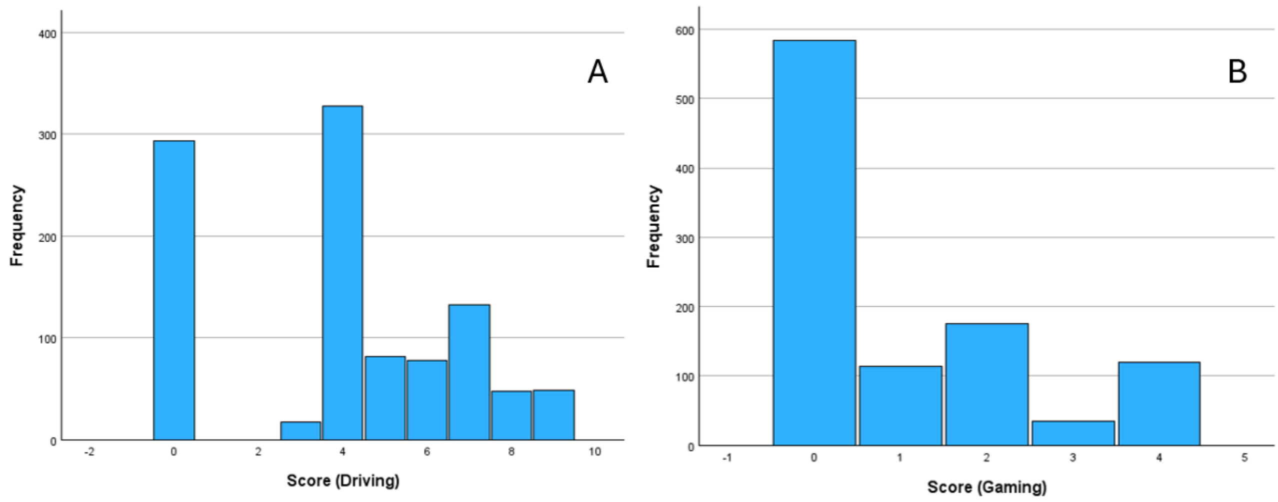
Distributions of Predictors



Note. (A) Distribution of the predictor Mean Pupil Change. The X-axis shows the change in Mean Pupil Change (Z-scored) and the Y-axis shows the frequency. (B) Distribution of the predictor Squared Pupil Dilation Change. The X-axis shows the change in squared mean pupil dilation change and the Y-axis shows the frequency.

Figure 4

Distribution of Confounder Variables



Note. (A) The distribution of the driving scores. The X-axis represents the driving score, and the Y-axis is the frequency of these scores. (B) The distribution of the gaming scores. On the X-axis the gaming scores can be seen, and the Y-axis shows their frequency.

Testing for Clustering

An intercept-only model, or null model, was estimated in order to evaluate the presence of clustering in the data. Only the random intercepts were included in this model, which allowed to get an estimate of the intraclass correlation.

Table A3 in the appendix displays the intercept-only model's findings. The variance of the intercept was .53 and significant $Z= 2.715$, $p=.0035$, with a standard error of .20. Since the test is significant, the null hypothesis that the variance is equal to zero was rejected. This provides evidence for significant variability between the intercepts suggesting that the clustering by participants should be accounted for in subsequent models. The intraclass correlation coefficient provides further evidence for clustering. ICC =.529/ (.529+3.29) =0.14.

Mixed-Effects Logistic Regression

The results of the mixed-effects logistic regression analysis are summarized in Table 2. The model included mean pupil change, the square of mean pupil change, driving experience, and gaming experience as predictors of the binary outcome. The model: log (P (positive outcome)/ (1−P (positive outcome)) = $b_0 + b_1$(pupil change) + b_2(pupil change^2) + b_3(Driving Experience) + b_4(Gaming Experience)

The analysis tested the following hypotheses:

H_0 (Quadratic Term): The square of the mean pupil change does not significantly predict the likelihood of a positive outcome in the driving task or lead to an increase in logits. H_0: $b_2 \geq 0$

H_1 (Quadratic Term): The square of the mean pupil change significantly predicts the likelihood of a negative outcome in the driving task (by leading to a decrease in logits). H_1: $b_2 < 0$

Mean Pupil Change: The coefficient for mean pupil change (b = -.11, SE = .10, p = .26) was negative, indicating that for a one unit increase in pupil change the log odds of a positive outcome decreased by -.11 units. However, this effect was not significant.

(Mean Pupil Change) ^2: The coefficient for the quadratic term (b = -.14, SE = .05, p = .00) was negative and significant, confirming the expected parabolic relationship between pupil change and performance outcome. With every one unit increase in Squared Pupil Change there was a decrease of -.14 in the participants' logits.

Driving Experience: The coefficient for driving experience (b = -.04, SE = .07, p = .54) was negative and non-significant.

Gaming Experience: The coefficient for gaming experience (b = .20, SE = .14, p = .172) was positive and non-significant.

The variances of random effects for all the predictors were not statistically significant. Driving: σ^2=.02, SE = .02, Z = 1.02, p = .3; Gaming: σ^2 = 7.197E-10[a]; Mean Pupil Change: σ^2 = 0.31, SE = 0.48, Z = 0.65, p =.52; Squared Pupil Change (SPC): σ2 = 1.512E-11[a].

Table 2

Mixed-Effects Logistic Regression Results

Fixed effects	Coefficient	Std. Error	T-test	Sig.
Intercept	.56	.37	1.53	.13
Score Driving (SD)	-.04	.07	-.62	.54
Score Gaming (SG)	.20	.14	1.37	.17
Mean Pupil Change (MPC)	-.11	.10	-1.14	.26
Squared Pupil Change (SPC)	-.14	.05	-2.85	.00
Random effects			Z-score	
σ^2_{SD}	.02	.02	1.02	.31
σ^2_{SG}	7.197E-10[a]	.	.	.
σ^2_{MPC}	0.31	0.48	.65	.52

σ^2_{SMPC}	1.512E-11[a]	.	.	.

Note. n=27

The mixed-effects logistic regression model showed a marginal R^2 of .04 and a conditional R^2 of .17, indicating that the fixed effects explain 3.8% of the variance in the outcome variable, while the combination of fixed and random effects explains 17.4% of the variance. Refer to Table A4 in the appendix.

Results: Correlation Analysis

The Correlation analysis was performed to test the hypotheses that anxiety traits negatively influence a person's driving performance and that higher levels of anxiety are associated with larger average pupil dilation change. First, the descriptive statistics of the used variables are presented, followed by the results of the first correlation analysis testing the influence of anxiety traits on driving performance and lastly the results of the second correlation analysis that looked at the association between anxiety levels and average pupil dilation change.

Measures

Participants completed between 15 and 64 trials, with an average of 38.11 trials (SD = 13.38). The success rate of passing cars varied from 17% to 82%, with an average success rate of 57.83% (SD = 19.52). The overall mean change in pupil size for each participant ranged from -.26 to 1.29, with an average change of .38 (SD = .47). Anxiety levels were assessed before the experimental task using a standardized questionnaire, with scores ranging from 0 to 18 and an average score of 6.56 (SD = 5.39). Refer to Table 3 for descriptive statistics and to Figure 5 for the distributions of the variables.

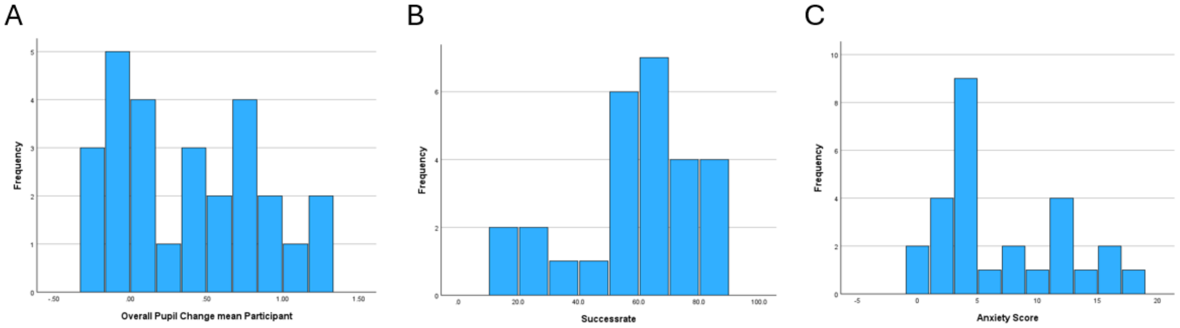
Table 3

Descriptive Statistics for the Variables

	N	*Minimum*	*Maximum*	*Mean*	*Std. Deviation*
Number of Trials	*27*	*15*	*64*	*38.11*	*13.38*
Success rate	*27*	*17*	*82*	*57.83*	*19.52*
Overall Pupil Change Mean Participant	*27*	*-.26*	*1.29*	*.38*	*.47*
Anxiety Score	*27*	*0*	*18*	*6.56*	*5.39*

Figure 5

Distributions of the Variables



Note. Distributions of the correlation analyses variables. (A) Distribution of the Overall Pupil Change mean. X-axis shows the mean pupil dilation changes of participants, and the Y-axis shows the frequency of them. (B) Distribution of Success Rates. X-axis shows the success rate scores and the Y-axis shows their frequency. (C) Distribution of anxiety scores. X-axis shows the anxiety scores and the Y-axis shows their frequency.

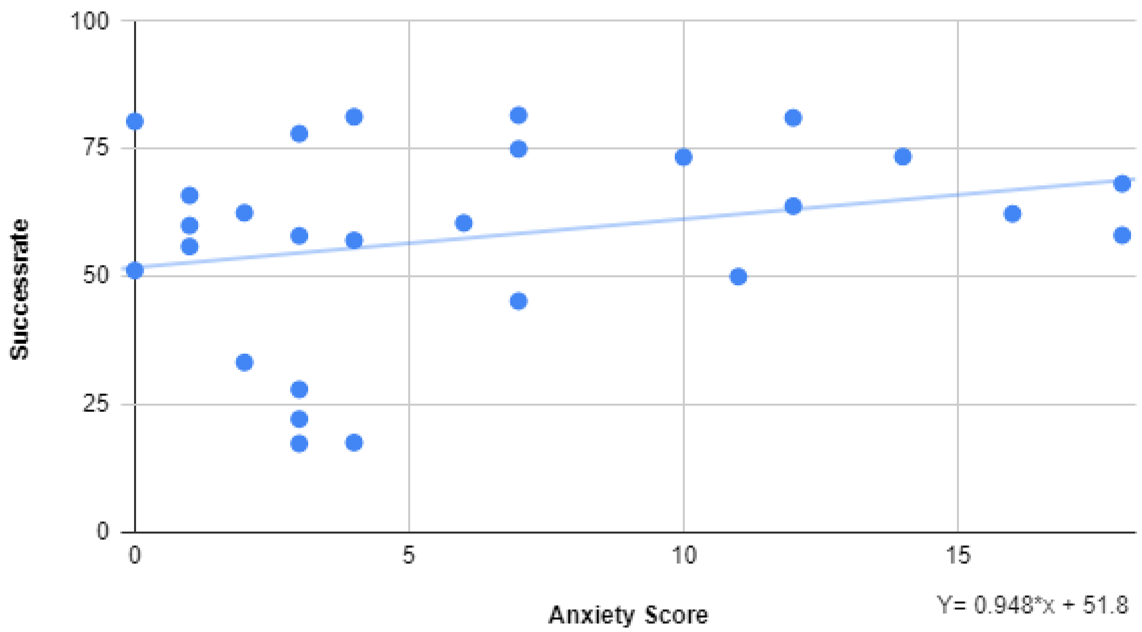
Correlation Analysis 1

The null hypothesis for the first correlation analysis was: there is no significant correlation between anxiety scores (A) and the success rate (S) on the driving task or that the association is positive. H_0: $\rho_{A,S} \geq 0$, where $\rho_{A,S}$ was the correlation coefficient between anxiety scores and success rate. The alternative hypothesis was that anxiety traits negatively influence a person's driving performance, indicated by a significant negative correlation between anxiety scores (A) and the success rate (S) on the driving task. H1: $\rho_{A,S} < 0$

The Pearson correlation method revealed that there was no significant linear correlation between anxiety scores and success rate $r(27) = -.16$, $p = .21$. There was insufficient evidence to reject the null hypothesis. Correlation table can be found in Table A5 in the appendix and a scatterplot in Figure 6.

Figure 6

Scatterplot: Success rate (Y-axis) and Anxiety Score (X-axis)



Note. Scatterplot with Success Rate on the Y-axis and the Anxiety Score on the X-axis, with a linear regression line. Each dot represents a participant. The formula of the regression line Y is shown at the bottom right corner.

Spearman Correlation analysis was performed to check for non-linear correlation between anxiety and success rate. There was no significant correlation between anxiety and success rate, r (27) = -.18, p =. 19. Refer to Table A6 in the appendix for the results.

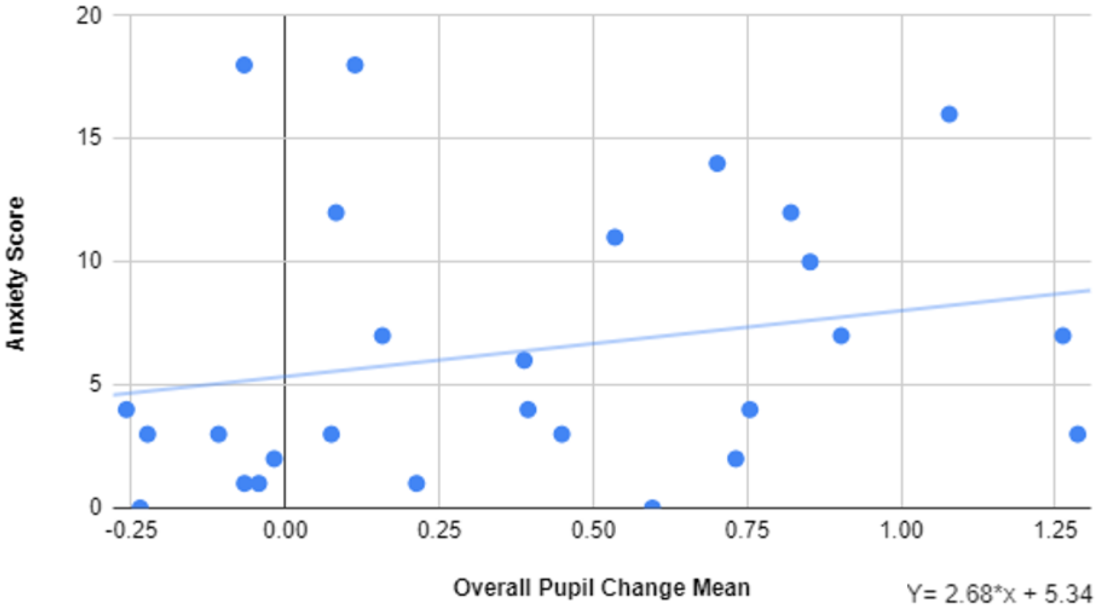
Correlation Analysis 2

The second correlation analysis's null hypothesis was that there is no significant correlation between GAD-7 anxiety scores and average pupil dilation change or there is a negative association between these variables. H_0: $\rho_{A,P} \leq 0$. The alternative hypothesis was that higher levels of anxiety, are associated with a larger average pupil dilation during the continuous driving task, indicated by a positive correlation between anxiety and average pupil dilation change. H_1: $\rho_{A,P} > 0$.

The Pearson correlation found no significant linear relationship between anxiety scores and Overall Pupil Change Mean r (27) = .06, p = .38 was found. The null hypothesis was not rejected. Correlation table can be found in Table A7 in the appendix and a scatterplot Figure 7. A further Spearman analysis found no non-linear correlation between Anxiety scores and Overall Pupil Change Mean r (27) = .06, p = .39. See Table A8 in the appendix.

Figure 7

Scatterplot: Overall Pupil Change Mean Participant (Y) and Anxiety Score (X)



Note. Scatterplot with Anxiety Score on the Y-axis and the Anxiety Score on the X-axis, with a linear regression line. Each dot represents a participant. The formula of the regression line Y is shown at the bottom right corner.

Discussion & Conclusion

The present study tried to answer the following research questions: 1) can pupil dilation as a measure of cognitive load predict the performance on a continuous driving task? 2) how does anxiety influence pupil dilation as a measure of cognitive load and predict performance on a continuous driving task? This was done by testing 27 participants. First, they had to fill in a GAD-7 anxiety questionnaire and then they were invited to the Cognitive Neuropsychology lab, where their pupil dilation changes were recorded during a continuous driving task.

To answer the research questions and to test the hypotheses, mixed-effects logistic analysis and correlation analyses were performed on the collected data. The first analysis tested the first hypothesis: 1) moderate pupil dilation change, defined as those changes that fall within the interquartile range (IQR) of the data distribution, during a trial will lead to more positive outcomes on the driving task (which serves as a measure of driving performance), while a bigger change in pupil dilation will result in a negative outcome on the driving task. The analysis revealed that the squared pupil change had a significant negative effect on driving performance, while the other predictors (gaming score, driving score and mean pupil dilation) did not have significant influence on the outcome variable. Therefore, the results supported the hypothesis that moderate pupil dilation changes or less cognitive load are associated with positive outcomes, whereas larger changes or high/low levels of cognitive load are more likely to lead to negative outcomes and pupil dilation as a measure of cognitive load can predict the performance on a continuous driving task. The results are in accordance with past studies that claim that both excessively high and low cognitive load can lead to poor performance by negatively affecting working memory (Vanneste et al., 2020).

The correlation analyses revealed that: 1) there was no significant correlation between anxiety scores and driving performance 2) there was no notable link between anxiety levels and mean pupil diameter change. Therefore, the results do not support the hypothesis that anxiety traits negatively influenced a person's driving performance, as indicated by a negative correlation between anxiety scores and the success rate. Also, we did not find evidence in support of the hypothesis that high levels of anxiety were associated with a larger average pupil dilation, indicating greater cognitive load during the continuous driving task. According to the results of the analyses, anxiety does not influence pupil dilation as a measure of cognitive load and does not predict performance on a continuous driving task. These results are not in accordance with the existing literature claiming that anxiety can decrease working memory capacity, leading to higher cognitive load and a decline in performance (Vytal et al., 2013). Although, the literature also suggests that under tough conditions anxious individuals may be able to find a way to improve their performance, which might explain the results of the analysis (Moran, 2016).

Multiple factors should be considered when interpreting the results of the correlation analyses. Firstly, the results might be not representative of the actual relationship between anxiety, pupil dilation change and the success rate, due to a small sample size, which can lead to insignificant results despite an actual relationship existing, due to being underpowered. Secondly, there might be other confounding variables that can affect driving performance that were not accounted for (e.g. how much rest the participant had the day before). Thirdly, the accuracy for measurements varied. The anxiety scores were not evenly distributed, with most participants scoring low on anxiety and only a few having high scores on the variable. This could have led to an under-representation of people with more anxiety traits compared to people with less anxious traits. In addition to this, the number of trials per participant varied, leaving some success rate measures more accurate than others. Fourthly, as for the purpose of the correlation analyses the raw data was aggregated, meaning that the power of the analysis diminished and became less sensitive to detecting meaningful patterns. Lastly, the relationship between the variables might be more complex and was therefore not captured by correlation analyses looking for linear and monotonic associations.

Additionally, the sample for both analyses did not include a wide range of participants, therefore lacking diversity. It mostly consisted of female psychology students between the ages 18 and 32. Leaving many groups underrepresented.

Although the mixed-effects analysis results are in accordance with the literature the following limitations of the study should be considered as well. Firstly, as mentioned before the sample size of the study was relatively small and uniform, therefore the generalizability of the findings is limited. Secondly, the model accounted for a relatively small variability in the outcome, with fixed effects explaining around 3.8%. Thirdly, the binary classification of the outcome (positive, negative) simplifies the complexity of driving behavior. Lastly, other physiological measures that could potentially influence driving performance (e.g. subjective stress level) were not looked at.

The strengths of the study lie in the reliability and robustness of the data that was achieved through removal of gaps, interpolation of eyeblink events, synchronization of eye tracking data with event triggers (ensuring temporal alignment) and utilization of both state and eye-tracking data. Another strength was that the use of a mixed-effects logistic regression provided a nuanced understanding of the factors influencing driving performance, examining both the fixed and random effects. Additionally, by using both the Pearson and Spearman correlation analysis to answer the second research question, a more in-depth understanding of the relationship between variables was achieved as both linear and non-linear relationships were explored.

All in all, this study provided insights into the physiological underpinnings of cognitive states during driving and showed how cognitive load can impact driving behavior. Additionally, the identification of physiological markers (e.g. pupil dilation) that can predict driving performance can contribute to the development of advanced driver-assistance systems and help in the creation of interventions aimed at improving driving safety and reducing accidents. However, further research is needed to assess the relationship between anxiety, mean pupil dilation changes and driving performance, as well as pupil dilation change and driving performance, which ensures adequate power (e.g. including more participants), looks at a more diverse group of people, and looks at possible confounders and interactions. Additionally, future research investigating the relationship between pupil dilation, as a measure of cognitive load and driving performance, would benefit from the incorporation of other physiological measures, and the examination of longitudinal effects (e.g. learning effects), and improving the ecological validity of the study by using a VR setting.

In conclusion this study examined the effects of cognitive load and anxiety on driving performance and found that pupil dilation change as a measure of cognitive load could predict performance on a driving task, while anxiety could not. Further studies are needed with bigger and more diverse sample.

Reference list

Anxiety. (n.d.). APA Dictionary of Psychology. Retrieved April 13, 2024, from https://dictionary.apa.org/anxiety

Chai, W. J., Abd Hamid, A. I., & Abdullah, J. M. (2018). Working memory from the psychological and neurosciences perspectives: A Review. *Frontiers in Psychology, 9*. https://doi.org/10.3389/fpsyg.2018.00401

Cowan, N. (2013). Working memory underpins cognitive development, learning, and Education. *Educational Psychology Review*, *26*(2), 197–223. https://doi.org/10.1007/s10648-013-9246-y

Deck, C., & Jahedi, S. (2015). The effect of cognitive load on Economic Decision Making: A Survey and new experiments. *European Economic Review*, *78*, 97–119. https://doi.org/10.1016/j.euroecorev.2015.05.004

Delpino, F. M., da Silva, C. N., Jerônimo, J. S., Mulling, E. S., da Cunha, L. L., Weymar, M. K., Alt, R., Caputo, E. L., & Feter, N. (2022). Prevalence of anxiety during the COVID-19 pandemic: A systematic review and meta-analysis of over 2 million people. *Journal of Affective Disorders*, *318*, 272–282. https://doi.org/10.1016/j.jad.2022.09.003

Hess, E. H., & Polt, J. M. (1964). Pupil size in relation to mental activity during simple problem-solving. *Science*, *143*(3611), 1190–1192.https://doi.org/10.1126/science.143.3611.1190

I-Jung, C., & Chi-Cheng, C. (2009). Cognitive Load Theory: An Empirical Study of Anxiety and Task Performance in Language Learning. *Electronic Journal of Research in Educational Psychology*, *7*. https://doi.org/10.14204/ejrep

Kahneman, D., & Beatty, J. (1966). Pupil diameter and load on memory. *Science*, *154*(3756), 1583–1585. https://doi.org/10.1126/science.154.3756.1583

Kahneman, D. (2011). *Thinking, fast and slow.* Farrar, Straus and Giroux.

Kolb, B., Whishaw, I. Q., & Teskey, G. C. (2019). *An introduction to brain and behavior* (6th ed.). Worth Publishers/Macmillan Learning.

Lansdown, T. C., Brook-Carter, N., & Kersloot, T. (2004). Distraction from multiple in-vehicle secondary tasks: Vehicle Performance and Mental Workload implications. *Ergonomics, 47*(1), 91–104. https://doi.org/10.1080/00140130310001629775

Mathers, C., Stevens, G., Hogan, D., Mahanani, W. R., & Ho, J. (2018). Global and regional causes of death: patterns and trends, 2000–15.

Moran, T. P. (2016). Anxiety and working memory capacity: A meta-analysis and narrative review. *Psychological Bulletin*, *142*(8), 831–864. https://doi.org/10.1037/bul0000051

Remes, O., Brayne, C., van der Linde, R., & Lafortune, L. (2016). A systematic review of reviews on the prevalence of anxiety disorders in adult populations. *Brain and Behavior*, *6*(7). https://doi.org/10.1002/brb3.497

Robinson, O. J., Vytal, K., Cornwell, B. R., & Grillon, C. (2013). The impact of anxiety upon cognition: Perspectives from human threat of shock studies. *Frontiers in Human Neuroscience*, *7*. https://doi.org/10.3389/fnhum.2013.00203

Sarason, I. G. (1988). Anxiety, self-preoccupation and attention. *Anxiety Research*, *1*(1), 3–7. https://doi.org/10.1080/10615808808248215

Szulewski, A., Gegenfurtner, A., Howes, D. W., Sivilotti, M. L., & van Merriënboer, J. J. (2016). Measuring physician cognitive load: Validity evidence for a physiologic and a psychometric tool. *Advances in Health Sciences Education*, *22*(4), 951–968. https://doi.org/10.1007/s10459-016-9725-2

van der Wel, P., & van Steenbergen, H. (2018). Pupil dilation as an index of effort in Cognitive Control Tasks: A Review. *Psychonomic Bulletin & Review*, *25*(6), 2005–2015. https://doi.org/10.3758/s13423-018-1432-y

Vanneste, P., Raes, A., Morton, J., Bombeke, K., Van Acker, B. B., Larmuseau, C., Depaepe, F., & Van den Noortgate, W. (2020). Towards measuring cognitive load through multimodal physiological data. *Cognition, Technology & Work*, *23*(3), 567–585. https://doi.org/10.1007/s10111-020-00641-0

Vytal, K. E., Cornwell, B. R., Letkiewicz, A. M., Arkin, N. E., & Grillon, C. (2013). The complex interaction between anxiety and cognition: Insight from spatial and verbal working memory. *Frontiers in Human Neuroscience*, *7*. https://doi.org/10.3389/fnhum.2013.00093

Wang, Q., Smythe, D., Cao, J., Hu, Z., Proctor, K. J., Owens, A. P., & Zhao, Y. (2023). Characterisation of cognitive load using machine learning classifiers of Electroencephalogram Data. *Sensors*, *23*(20), 8528. https://doi.org/10.3390/s23208528

Zhang, H., Guo, Y., Yuan, W., & Li, K. (2023). On the importance of working memory in the driving safety field: A systematic review. *Accident Analysis & Prevention*, *187*, 107071. https://doi.org/10.1016/j.aap.2023.107071

Appendix

Table A1

Trial Time (ms)

	N	Range	Minimum	Maximum	Mean	Std. Deviation

Epoch Time	1029	48715	715	49430	11079.52	7440.48

Table A2

Dependent Variable Descriptives

			N	Percent
Dependent Variable	Outcome	0	386	37.5%
		1	643	62.5%
		Total	1029	100%

Table A3

Results of the Test for Clustering

Random Effect	Estimate	Std. Error	Z	Sig.
Var(Intercept)	.529	.195	2.715	.007

Table A4

Coefficients of Determination

Pseudo-R Square	Marginal	.038

Measures	Conditional	.174

Note. Observation-level variance estimated via delta method.

Table A5

Pearson Correlation Analysis Results for Variables Success Rate and Anxiety Score

Success rate	Pearson Correlation	1	-.163
	Sig. (1-tailed)		.208
	N	27	27
Anxiety Score	Pearson Correlation	-.163	1
	Sig. (1-tailed)	.208	
	N	27	27

Table A6

Spearman Correlation Analysis Results for Variables Success Rate and Anxiety Score

			Success rate	Anxiety Score
Spearman's rho	Success rate	Correlation Coefficient	1.000	-.177
		Sig. (1-tailed)	.	.189
		N	27	27

	Anxiety Score	Correlation Coefficient	-.177	1.000
		Sig. (1-tailed)	.189	.
		N	27	27

Table A7

Pearson Correlation Analysis Results for Variables Overall Pupil Change Mean Participant and Anxiety Score

		Anxiety Score	Overall Pupil Change Mean Participant
Anxiety Score	Pearson Correlation	1	.064
	Sig. (1-tailed)		.375
	N	27	27
Overall Pupil Change mean Participant	Pearson Correlation	.064	1
	Sig. (1-tailed)	.375	
	N	27	27

Table A8

Spearman Correlation Analysis Results for Variables Overall Pupil Change Mean Participant and Anxiety Score

			Anxiety Score	Overall Pupil Change Mean Participant
Spearman's rho	Anxiety Score	Correlation Coefficient	1.000	.055
		Sig. (1-tailed)	.	.393
		N	27	27
	Overall Pupil Change Mean Participant	Correlation Coefficient	.055	1.000
		Sig. (1-tailed)	.393	.
		N	27	27