Relationship between peripheral indicators of arousal as indicators of attentional networks

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Author Note

This document contains the thesis project [27.5 ECTS] on the topic of spatial attention, the orienting response and the Drift Diffusion Model (DDM). The thesis was supervised by Christoph Strauch.

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Abstract

The Drift Diffusion Model (DDM) has long been used to investigate perceptual decision making. Previous research has linked pupil size measures to decision making processes, which in turn were linked to parameters of the DDM (Strauch et al., 2022b; de Gee et al., 2014; Murphy et al., 2014). Little research has been done to pair the DDM to the orienting response, a spatial component of pupil size. This research attempts to investigate the relationship between the orienting response (spatial decision making) and parameters of the DDM. We used a spatial decision-making paradigm in which participants indicated which Gabor patch (left or right) was larger. The Gabor patches were laid over black- and white bars for 200ms at the start of a trial to induce a pupil light reflex. This allowed us to measure the degree of spatial attention (Strauch et al., 2022a). We found pupil constriction to be a significant predictor of RT as well as accuracy. Stronger pupil constriction indicated longer RT and lower accuracy. We additionally replicated previous findings by Murphy et al. (2014), baseline pupil size positively predicts accuracy. These results show we can indeed link the orienting response to DDM parameters. To what specific DDM parameters these can be linked is a topic for future research.
Keywords: Drift Diffusion Model, pupillometry, spatial attention, orienting, alerting

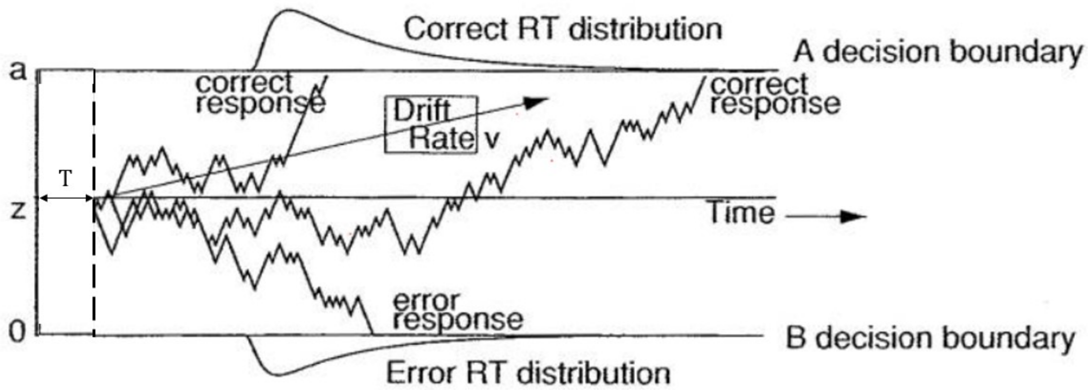
1. Introduction

Decision making is a high-level cognitive process based on perception, attention, and memory (Prezenski et al., 2017). It is also a process in which choices are made by gathering information and assessing alternatives. Studying these choices has been an integral part of cognitive psychology (Ratcliff & Smith, 2006). We gather sensory information from a set of alternatives and compute this information to come to an informed decision. Choices are often binary: 'yes or no', 'left or right', 'this or that' and are generally studied as such. Experimental psychology has predominantly used random dot motion paradigms (RDM) to study perceptual decision making (Britten et al., 1992; Forstmann et al., 2010; Mulder et al., 2010, 2013; Pilly & Seitz, 2009; van Maanen et al., 2011). Participants are required to gather, process and interpret visual information on the properties of the RDM, to make an informed decision about its physical properties. During the task, dots move randomly through a circle shaped field. The participant is required to indicate, when more than fifty percent of the dots are moving in the same direction. Tasks like the RDM return behavioral outcome measures such as reaction time (RT) and accuracy. These behavioral measures are frequently modeled with so-called drift diffusion models (DDM).

1.1 Drift Diffusion model

The DDM is the dominant model used to study decision making. It takes behavioral outcome measures (RT & accuracy), translating these into components of cognitive processing (Ratcliff & McKoon, 2009). The DDM uses a multitude of parameters amongst which are a starting point, non-decision time, boundary separation and drift rate (Figure 1). The *starting point (z)* is associated with a bias towards one of the choice alternatives. This is usually halfway between both decision boundaries but can be manipulated. By explicitly (cue) or implicitly (changing proportion) attending the participant to which option most likely holds the correct answer (Mulder et all., 2012). For spatial decisions, starting bias could also be related to pseudoneglect, as this presents an innate attentional bias towards the left-visual hemifield (Jewell & McCourt, 2000). The stronger the attentional bias, the larger the shift in starting point. Underlying attentional networks have been suggested to determine the degree of this attentional bias (Strauch et al., 2022b). *Non-decision time (T)* is thought to reflect peripheral processing, this includes motor response as well as processing of the scene and stimuli prior to information accumulation. It can be manipulated by increasing mental load (van Ravenzwaaij et al., 2011), but is often stable within an experiment. *Boundary separation* can be easily manipulated by instructing the participant about speed and accuracy. An emphasis on accuracy is thought to increase caution and in turn boundary separation (Ratcliff & McKoon, 2008). Lastly, *drift rate (v)* is calculated using the behavioral outcome measures. It is associated with difficulty and reflects the accumulated evidence for the choice (van Ravenzwaaij et al., 2011).

Figure 1
Graphical representation of DDM parameters



Note. The image shows three simulations using the DDM. Two drift towards the correct response, one drifts towards the incorrect response. Adapted from Ratcliff, R., & McKoon, G. (2008). The diffusion decision model: theory and data for two-choice decision tasks. *Neural computation*, *20*(4), 873-922.

1.2 Psychophysiology to understand decision making

It has been shown how powerful the DDM is for modeling decision making. If the DDM indeed reflects our decision-making processes, we should be able to isolate psychophysiological substrates of the parameters specified by the DDM. Amongst recent publications, pupil size is arguably the most promising psychophysiological measure with multiple links to separate parameters of the DDM (de Gee et al., 2014; Murphy et al., 2014; Luck, 2005; Poldrack et al., 2011).

Pupil size not only reflects changes in brightness and accommodation, but an array of mental processes (Naber et al., 2011, 2013; Strauch et al., 2022b). This includes changes in attention and high-level cognition. These changes in attention are linked to differential attentional networks (alerting, orienting, executive function). Pupil size changes linked to the alerting response are mediated by a network centered around the locus coeruleus (LC) and the norepinephrine system (Sara, 2009). The LC is non-spatially organized and elicits relatively slow responses compared to structures of other attentional networks (Strauch et al., 2022a.). De Gee et al. (2014) demonstrate a link between drift rate/evidence accumulation and pupil size *during* decision making. This is little surprising, given that the pupil closely tracks fluctuations in mental effort/memory load (Alneas et al., 2014). Furthermore, Murphy et al. (2014) demonstrated how baseline pupil size (thus *prior* to the decision-making process) is supposedly linked to increases in evidence accumulation rate (*drift rate*) variability. Changes in pupil linked arousal states thus affect the decision-making process.

The orienting response is a reflexive response evoked by novel stimuli (Sokolov, 1990). This response is modulated by the superior colliculus (SC), a spatially organized structure located in the posterior midbrain. The SC is known to play a critical role in the neural control of saccadic eye movements (King, 2004). As the SC and the orienting response are heavily linked, the orienting response has been suggested to determine the degree of the change in the deployment of spatial attention. The SC has since been described to likely mediate the pupil size changes caused by the attentional orienting response (Strauch et al., 2022a).

Executive functions, such as changes in focal attention, likely affect pupil size through use of both the LC- and SC systems (Joshi & Gold, 2020; Strauch et al., 2022b).

Components of the DDM have already been linked to the alerting networks through pupil size (Alneas et al., 2014; de Gee et al., 2014; Murphy et al., 2014). Here we set out to test whether pupil size can indicate a further parameter in the DDM, by investigating pupil size changes associated with orienting *in the beginning of* a decision-making process. We do this by using a spatial decision task in combination with pupillometry, in contrast to the more frequently used RDM tasks (Britten et al., 1992; Forstmann et al., 2010; Mulder et al., 2010, 2013; Pilly & Seitz, 2009; van Maanen et al., 2011). Though most decisions in life are spatial, RDM tasks are not (Mulder et al., 2013). As the orienting response relies heavily on the SC and this structure is spatially organized, a spatial task is needed to investigate it. Our pupils respond to changes in brightness (Binda & Gamlin, 2017). As Gabor patches can be set to equal brightness as background luminance, these stimuli are suited for pupillometry. The research will thus use Gabor patches of different sizes in a spatial organization (one left, one right) to investigate our hypotheses.

2. **Research question & hypotheses**

To what extent can the orienting response be linked to components of the DDM?

1. Pupil constriction is linked to behavioral outcome measures of the DDM.
   1A. Pupil constriction is a predictor for RT
   1B. Pupil constriction is a predictor for accuracy
2. Baseline pupil size should be predictive of accuracy.
3. If the orienting response indeed determines the degree of the attentional bias, this should influence the starting point for decision making.

3. Methods

3.1 Participants

A convenience sample of *n* = 19 participants took part in the experiment. Of these, five were discarded due to incomplete/unusable data. Data of *n* = 14 participants (M_{age} = 21.8, SD_{age} = 2.4) were used in the analyses. All participants read and agreed to an informed consent in which it was stated that the acquired data would be anonymized and handled confidentially. There were no negative consequences to participating in or aborting the experiment. Participants could decide to receive either € 6,- cash or 0.75 participation credit in line with the UU guidelines.

3.2 Materials

The experiment was conducted using PsychoPy version 2020.2.9 (Peirce et al., 2019) on an Asus ROG PG278Q monitor with a refresh rate of 99 Hz. The monitor featured a screen resolution of 2560*1440 pixels at 67.5cm distance from the participant. A standard keyboard was placed on the desk between monitor and participant. Gaze position and pupil size of the right eye were measured using an Eyelink 1000+ tracker (SR research) in a light- and sound-attenuated laboratory. A chin- and forehead rest was used to ensure stable head position.

3.3 Design and procedure

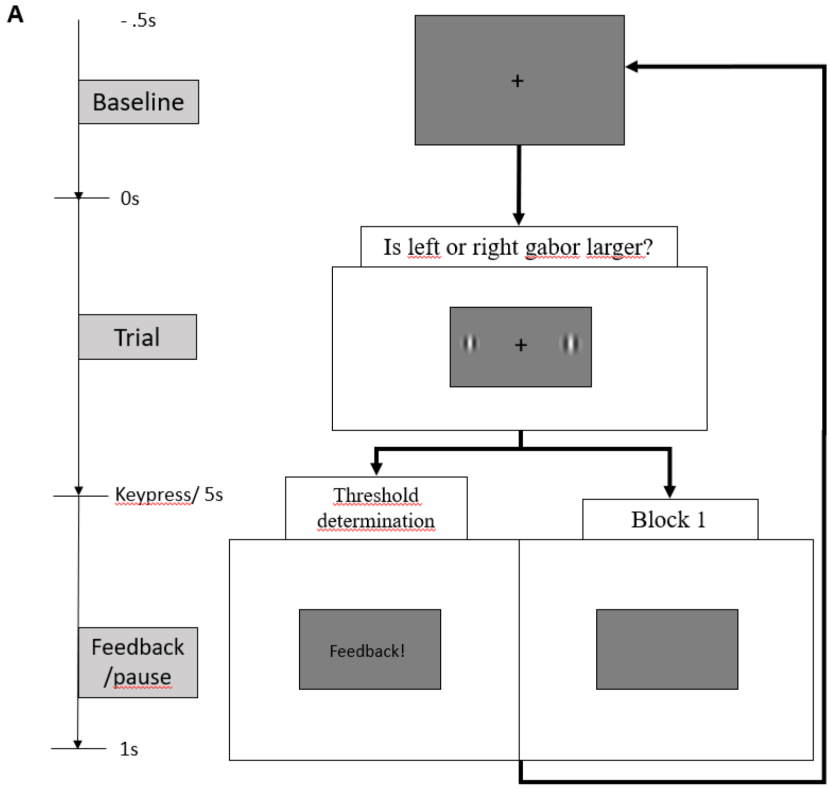
Before the experiment started, participants read an information letter and informed consent. After signing the informed consent and agreeing to participate in the experiment, set-up and length of the experiment were explained. Before starting the experiment, a nine-point calibration and validation procedure of the eye-tracker was performed. The experiment consisted of two parts for a total of three blocks. The first part of the experiment contained one block with 100 trials and was used to determine stimulus size difference for part two of the experiment (Figure 2A). Participants were instructed to attend and keep their gaze position at the center of the screen for more than 0.5 seconds to start a trial. A trial consisted of two Gabor patches with gaussian masks presented 1000 pixels (visual angle needs to be calculated) towards the left- and right side of the fixation cross. These circles had varying sizes, with a base size of 250 pixels. Stimulus size difference could either be: 5, 10, 15, 25 or 50 pixels. With size (up to twenty times per condition) and target side randomly selected each trial. Participants were required to keep their gaze position at the center while covertly attending the Gabor patches. Participants were instructed to react as fast and accurately as possible to which of the two patches was larger using the left and right arrow keys. Trials were self-paced with the trial ending after keypress, participants would additionally receive feedback on their performance after each trial. Stimuli were presented for a maximum of five seconds in case of no response. If gaze position was shifted from the center of the screen, or no response was given, a warning message would be displayed, and the trial would be recycled to be redone later. Participants would receive a message with the number of trials after each 25 correct trials. After completing 100 correct trials, participants could get out of the chinrest and take a mandatory five-minute break as the stimulus size difference was calculated.

The stimulus size difference for part two of the experiment was calculated with a proportional drift diffusion model (PRDDM) in Jupyter Notebook. Responses faster than 0.15 seconds and slower than 2 seconds were removed from the dataset. Using RT, accuracy and size difference, the model was fitted over the data. Stimulus size difference for a performance threshold of 80% was calculated and plotted, this threshold determined the difference between stimuli for the following two blocks.

Part two of the experiment consisted of two separate blocks with 125 trials each. Trials remained self-paced but the participants no longer received performance feedback. Experimental design of block 1 was equal to that of the threshold block with one exception (Figure 2A). The feedback screen was changed to a one second blank grey screen to remove aftereffects (Thompson & Burr, 2009) and allow time for blinking. Participants could take an additional break between blocks but were required to keep their head on the chinrest. Block 2 added a brief 200ms visual stimulus at the beginning of each trial (Figure 2). Black (<.15 cd/m^2) and white (42.5 cd/m^2) bars (width of 9° visual angle), randomly presented at the right or left of the screen respectively were presented behind the Gabor patches. Participants were again instructed to report which stimulus was larger and to respond as fast and accurately as possible.

After completion of both parts of the experiment, participants were thanked and debriefed on the aim of the research.

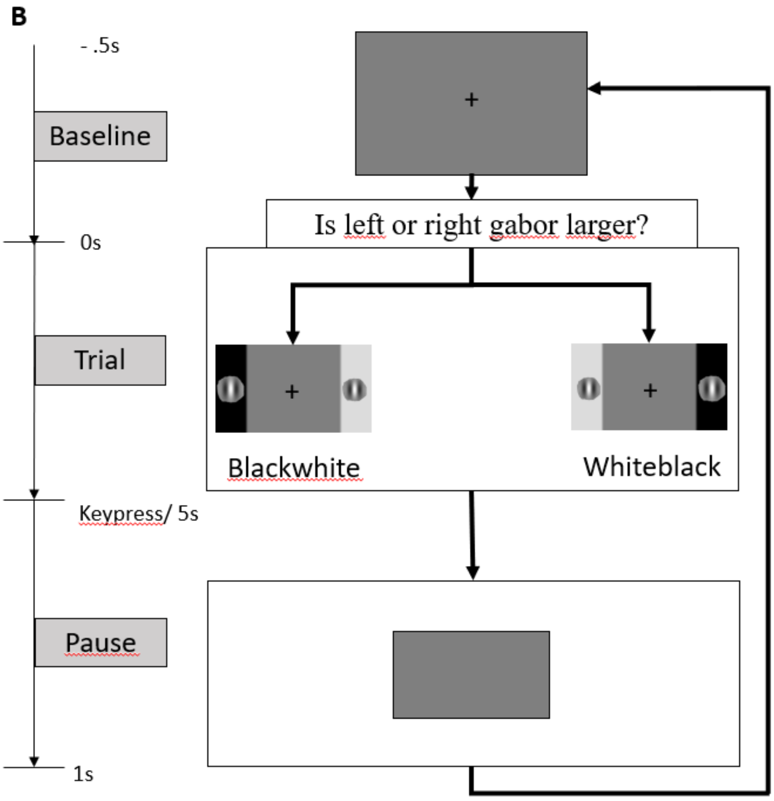
Figure 2A
Trial sequence threshold- & block 1



Note. Trials always started with a grey baseline screen, followed by a screen with two Gabor patches. After responding participants either received feedback in the 'threshold block' or a grey screen in block 1.

Figure 2B

Trial sequence block 2



Note. Trials always started with a grey baseline screen, followed by a screen with two Gabor patches. During the first 200ms of the trial screen, black/white bars in either configuration were layed under the Gabor patches. After response a one second grey pause screen was presented.

3.4 Stimuli

Each Gabor patch used in the experiment had a set of constant physical properties: [Texture: Sin, Mask: gauss, Phase (in cycles): 0.0, Spatial frequency: 0.012, Texture resolution: 128]

Gabor patches in part one of the experiment had varying sizes, with a base size of 250 pixels. Stimulus size difference could either be: 5, 10, 15, 25 or 50 pixels. With size (up to twenty times per condition) and target side randomly selected each trial.

3.5 Data processing

Data was processed using a custom-made Python script (3.7.9). Invalid trials were removed from the dataset. Pupil traces were baseline corrected by subtracting the average pupil size of the last 200ms before trial onset from every following data point.

4. Results

To investigate our hypotheses, two mixed linear models (MLM) were run. Results are split in three sections. In the first we predict RT, in the second section we predict accuracy, and in the third we present the measured pupil traces. Figure 5 shows pupil traces comparisons for the first and second block. It is evident that there is no pupil constriction in the first block, which is why there is little use in using this data to investigate the relationship between the orienting response and the DDM. The results will thus be focused on the second block. As the DDM has many components and behavioral measures linked to it, our prediction of RT as well as accuracy both attempt to answer our initial hypothesis.

4.1 Predicting reaction times

Both (MLM) regressions were run in Python using the statsmodel package (Seabold et al., 2010). Our first MLM included *RT* as the dependent variable, main effects for *accuracy*, *baseline pupil size*, *constriction amplitude* and a *squared component of the constriction amplitude* were added. *Participant* was included as a random effect. This model was chosen through the Akaike Information Criterion (AIC), as it had the lowest AIC value (Appendix A). A total of eight models to predict RT were tested. The model was specified as follows:

$$RT \sim accuracy + baseline\ pupil\ size + constriction\ amplitude + squared\ constriction\ amplitude + (1|Participant)$$

Results show a very large z-score for constriction amplitude, as well as a large z-score for accuracy (Table 1) with both being statistically significant.

Table 1

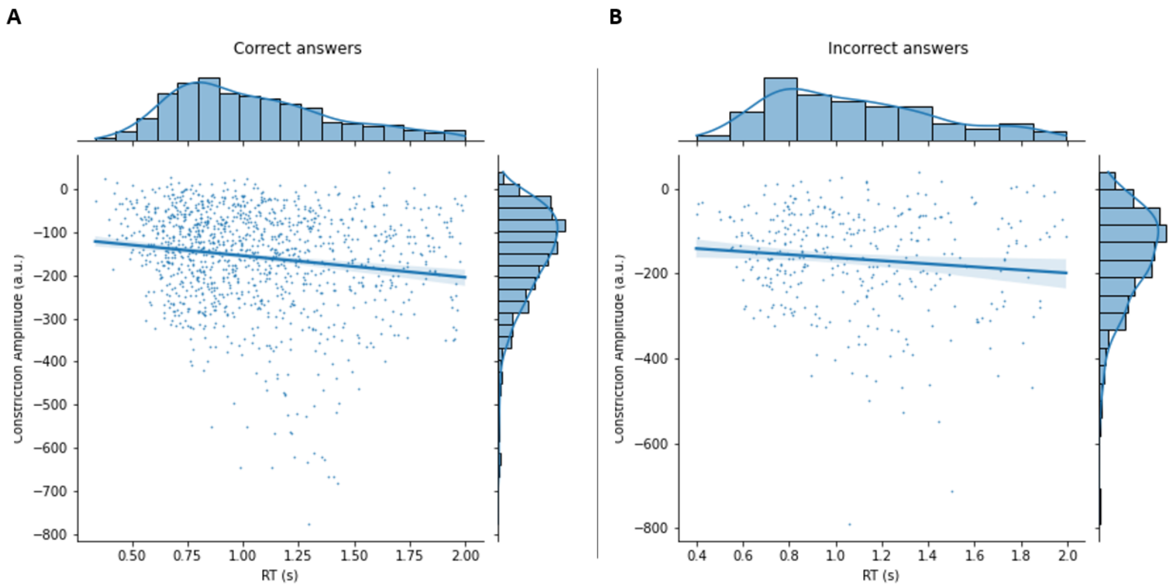
Fixed and random effects for the MLM with RT as the predicted variable.

Effect	Estimate	SE	*z*	*P Value*
Fixed:				
Intercept	1.131	0.085	13.300	0.000
Correct	-0.043	0.016	-2.622	0.009
Baseline Pupil Size	0.000	0.000	-1.630	0.103
Constriction Amplitude	-0.001	0.000	-3.846	0.000
Sq. Constriction Amplitude	0.000	0.000	-1.939	0.052
Random:				
Participant	0.060	0.085	----	----

A linear regression was calculated to predict RT based on constriction amplitude, for both correct- (Figure 3A) and incorrect (Figure 3B) answers. A significant regression was found for correct answers *($F(1, 1213) = 29.43$, $p < 0.001$)* with an R^2 of 0.024. Participants' predicted RT is equal to *0.9756 – 0.0005 x constriction amplitude* in seconds. A similar significant regression equation was found for incorrect answers *($F(1, 364) = 4.449$, $p<0.05$)* with and R^2 of 0.012. Participants' predicted RT is equal to 1.0270 - 0.0003 x *constriction amplitude* in seconds. For both correct and incorrect answers, the constriction amplitude related negatively to reaction time with slower reactions observed when the pupil constricted stronger.

Figure 3

Reaction time predicted by constriction amplitude

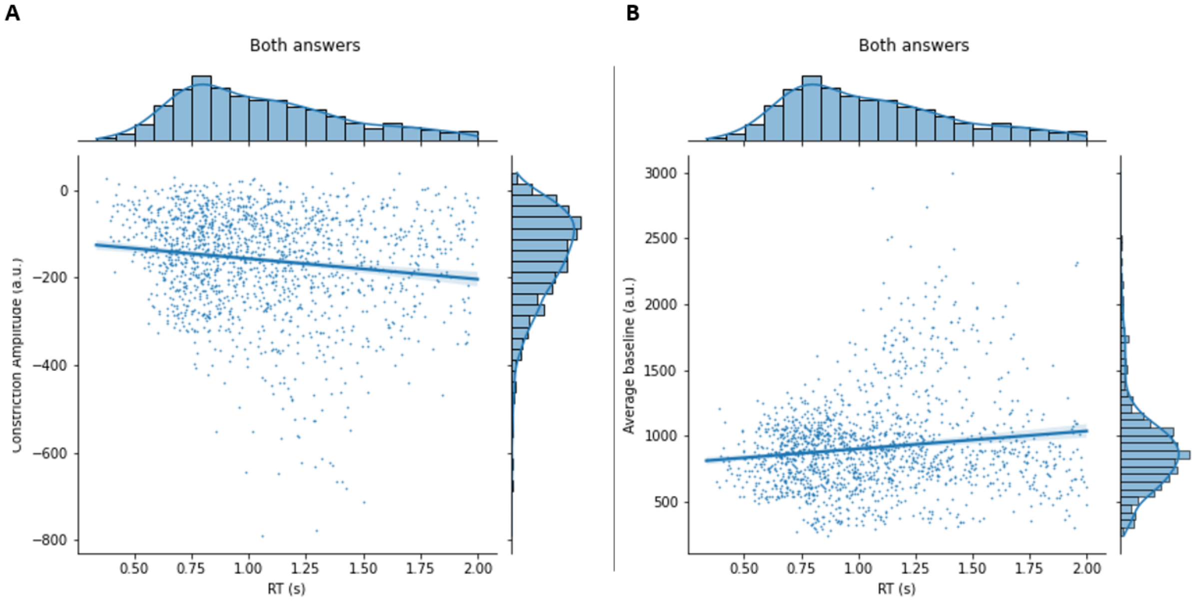


Note. Constriction amplitude is given in arbitrary units but can be defined as the difference between the absolute pupil constriction – average baseline pupil size. (A) RT predicted by constriction amplitude for correct answers. (B) RT predicted by constriction amplitude for incorrect answers.

A linear regression was calculated to predict RT based on constriction amplitude (Figure 4A) and baseline pupil size (Figure 4B). A significant regression equation was found for constriction amplitude *($F(1, 1579) = 33.59$, $p < 0.001$)* with an R^2 of 0.021. Participants' predicted RT is equal to *0.9870 – 0.0004 x constriction amplitude* in seconds. A similar significant regression equation was found for baseline pupil size *($F(1, 1579) = 30.66$, $p<0.001$)* with and R^2 of 0.019. Participants' predicted RT is equal to *0.9298 + 0.0001 x baseline pupil size* in seconds. Constriction amplitude related negatively to reaction time with slower reaction times observed when the pupil constricted stronger. The opposite was found for baseline pupil size, this related positively to reaction time with faster reaction time observed with a higher baseline pupil size.

Figure 4

Reaction time predicted by constriction amplitude vs. baseline pupil size



Note. Constriction amplitude and baseline pupil size are given in arbitrary units but can be defined as the difference between the absolute pupil constriction – average baseline pupil size. (A) RT predicted by constriction amplitude. (B) RT predicted by average baseline pupil size.

4.2 Predicting accuracy

Our second MLM included *accuracy* as the dependent variable, main effects for *baseline pupil size* and *constriction amplitude* were added. *Participant* was included as a random effect. This model was chosen through the Akaike Information Criterion (AIC), as it had the lowest AIC value (Appendix B). A total of four models to predict accuracy were tested. The model was specified as follows:

$$Accuracy \sim baseline\ pupil\ size + constriction\ amplitude + (1|Participant)$$

Results show both baseline pupil size and constriction amplitude to be significant predictors of accuracy (Table 2).

Table 2

Fixed and random effects for the MLM with accuracy as the predicted variable.

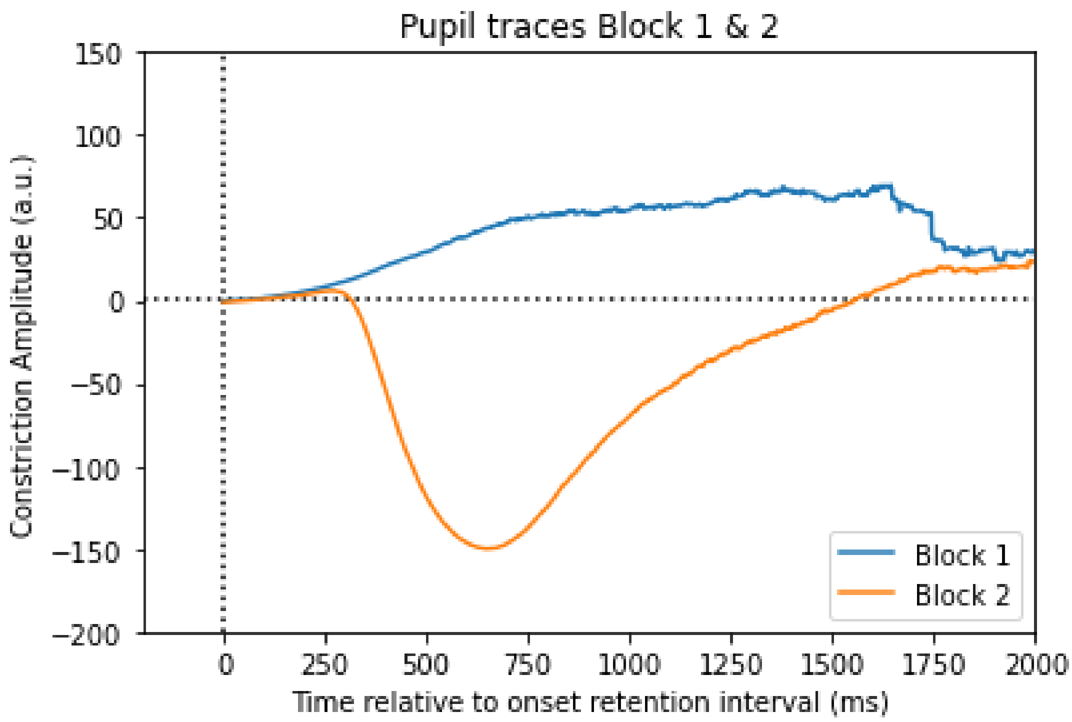
Effect	Estimate	SE	*z*	*P Value*
Fixed:				
Intercept	0.699	0.048	14.709	0.000
Baseline Pupil Size	0.000	0.000	2.195	0.028
Constriction Amplitude	0.000	0.000	2.367	0.018
Random:				
Participant	0.003	0.005	----	----

4.3 Pupil traces

Figure 5 shows the average pupil traces for block 1 and block 2. Average pupil traces in block 1 show a clear dilation, while average traces in block 2 show a constriction.

Figure 5

Average pupil traces for block 1 and block 2

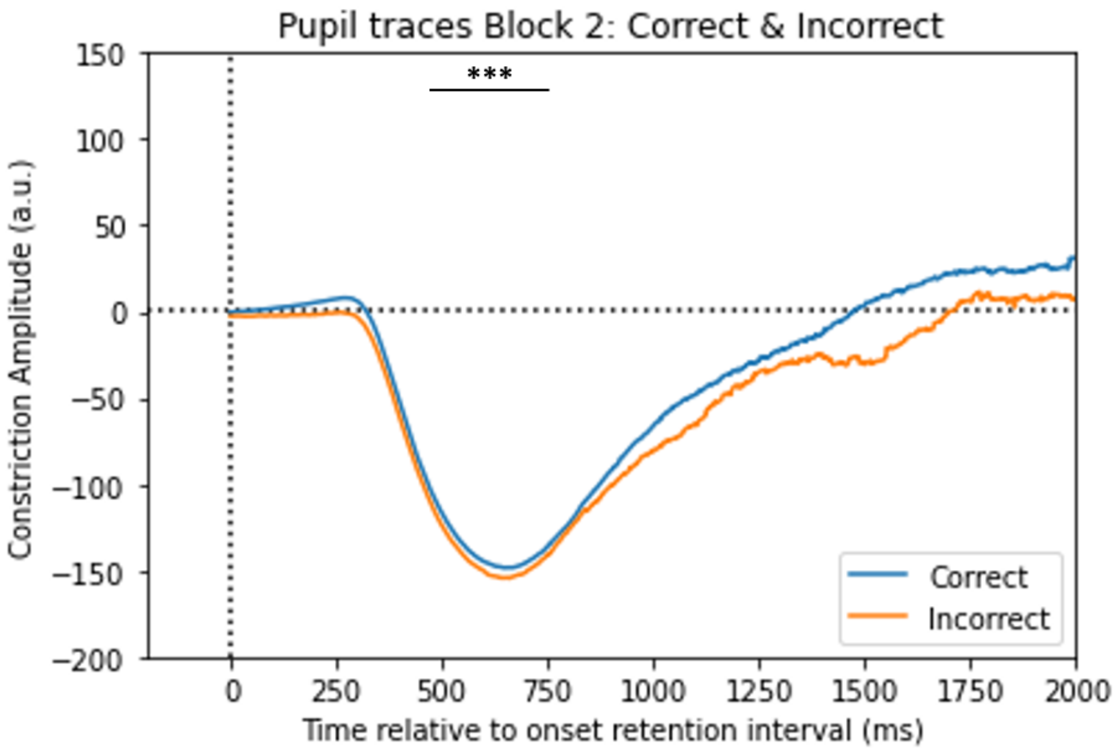


Note. Average pupil size relative to baseline in arbitray units (a.u.). Negative values on the y-axis indicate a smaller pupil size compared to the baseline featuring a grey screen.

A dependent samples t-test was run to investigate the maximum constriction difference between the pupil traces for correct- and incorrect answers (Figure 6). Maximum pupil constriction was calculated for both traces and a window of twenty data points (ten to each side) was taken as the array. The dependent t-test shows a significant difference between the pupil traces for correct- and incorrect answers, *t(19)=152.591, p<0.0001*.

Figure 6

Pupil traces for correct and incorrect answers



Note. Average pupil size relative to baseline in arbitray units (a.u.) for both *correct (blue)* and *incorrect (orange)* answers. Negative values on the y-axis indicate a smaller pupil size compared to the baseline featuring a grey screen. Participants had an average response time of 1185ms for correct answers and 1282ms for incorrect answers. As trials were self-paced, less data was collected at later time points. This explains the poorer data quality seen further along the x-axis. *** = $p < 0.0001$.

Discussion

The pupil's alerting response, mediated by the LC, has already been linked to components of the DDM (Strauch et al., 2022b). Pupil size *during* the decision-making process has been linked to *drift rate*/evidence accumulation (de Gee et al., 2014). As well as baseline pupil size (*before* the decision-making process) being linked to increases in *drift rate* variability (Murphy et al., 2014). In this research we investigated whether the pupil orienting response can also be linked to DDM components. The orienting response is mediated by the SC, which is a spatially organized neural structure. As the SC and orienting response are heavily linked, the response has already been suggested to determine the degree of the change in the deployment of spatial attention (Strauch et al., 2022b). Participants completed a spatial decision-making task, in which they indicated whether a Gabor patch presented on the left or the right was larger. This spatial decision-making task was used to adhere to the spatial organization of the SC (King, 2004). Whilst also fitting with demands of the DDM, as a binary forced choice paradigm (Ratcliff & Rouder, 2000). Here, we report several results demonstrating that the orienting response can indeed be linked to components of the DDM.

We found pupil constriction to be a significant predictor of RT ($p < 0.001$) as well as accuracy ($p < 0.05$). Stronger pupil constriction indicates longer RT (Figure 4, Figure 5A) and lower accuracy. These findings are in line with our hypotheses as they show we can link the orienting response to the DDM. As well as offering an insight into the influence of the strength of the orienting response in combination with those parameters. Figure 3 shows constriction amplitude to be a negative predictor for RT irrespective of accuracy. Regression equations show a negative value per unit of constriction amplitude. This is because, though there is an increase in constriction amplitude, this is measured as a decrease in pupil size. We additionally found baseline pupil size to positively predict RT (Figure 4B). This is in line with our hypothesis, as well as previous findings by Murphy et al., (2014). Our second MLM (Table 2) shows both *constriction amplitude* (as mentioned above) and *baseline pupil size* to be slightly positive predictors of accuracy.

Figure 6 shows a stronger pupil constriction for incorrect answers compared to correct answers ($p<0.0001$). If there is a strong orienting response (large constriction amplitude), one would assume a fast deployment of spatial attention (Strauch et al., 2022a). This spatial attention is required to come to a decision as we need to attend either side. We thus need to first deploy spatial attention and, if the pupil indexes this, it is conceivable the starting point in the DDM model changes with this. This reduces the distance to either one of the boundaries, likely reducing time needed to come to the decision associated with this boundary. However, it is also possible we show a strong orienting response if our spatial attention is at an incorrect position. In this case, a strong orienting response should be associated with *slower* responses. Though we see a stronger orienting response, our results also show an increase in RT for incorrect answers. This leaves room for speculation about the effect of both the orienting and alerting response on the eventual RT. If a stronger orienting response is indeed accompanied by a shift in *starting point*, this may be countered by the effect of mental effort *during* the decision-making process (de Gee et al., 2014; Alneas et al., 2014).

Though fitting the actual model is outside of the scope of this thesis, a next step in future research would be to link this orienting response to specific parameters of the DDM. *Drift rate* is unlikely to be linked to the orienting response, as it was already linked to pupil dilation (de Gee et al., 2014). As well as *boundary* separation, as this has been found to be manipulated by task instruction (Ratcliff & McKoon, 2008). As stated, it is very conceivable *starting point* could be linked to the orienting response. Fitting the model would possibly explain any confusion on the strength of the effect of both the orienting and alerting response. Perhaps *non-decision time* could also be linked to the orienting response, as it also reflects internal mental processes (van Ravenzwaaij et al., 2011). This would carry our third hypothesis over into a new research in which the model is fitted to the data.

As our first block has proven to be non-informative for the orienting response, there is little use in keeping it in the experimental design. Without this first block, the number of trials in the 'threshold block' and block 2 could be increased. An increased amount of trials in the 'threshold block' subsequently increases sensitivity of the PRDDM, leading to a better threshold value and a more accurate experiment. Additionally, the current paradigm has a base value for either the left-or right Gabor patch (250 pixels). The other Gabor patch is always larger by the number of pixels calculated in the 'threshold block'. Participants are not informed on this, but it is possible they perceived it somewhere in the experiment. It is highly unlikely this was the case, as all participants reported to have found the task very difficult. As the threshold is calculated for the 250-pixel Gabor patch, an increase/decrease of this base size would alter the relative threshold. It would be better to randomly select whether the alternative is smaller or larger than the baseline size. This ensures participants cannot be sure about the correct answers without attending both sides of the screen.

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