Individual differences in working memory capacity, attention control, fluid intelligence, and
pupillary measures of arousal

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Abstract

The present study examined individual differences in three cognitive abilities: attention control (AC), working memory capacity (WMC), and fluid intelligence (gF) as they relate the tendency to experience task-unrelated thoughts (TUTs) and the regulation of arousal. Cognitive abilities were measured with a battery of nine laboratory tasks, TUTs were measured via thought probes inserted into two tasks, and arousal regulation was measured via pupillometry. Recent theorizing (Robison & Unsworth, 2017a) suggests that one reason why some people experience relatively frequent TUTs and relatively poor cognitive performance - especially AC and WMC - is that they exhibit dysregulated arousal. Here, we examined how arousal regulation might predict both AC and WMC, but also higher-order cognitive abilities like gF. Further, we examine direct and indirect associations with these abilities via a mediating influence of TUT. Participants who reported more TUTs also tended to exhibit poorer AC, lower WMC, and lower gF. Arousal dysregulation correlated with more TUTs and lower AC. However there was no direct correlation between arousal regulation and WMC, nor between arousal regulation and gF. The association between arousal regulation and gF was indirect via TUT. We discuss the implications of the results in light of the arousal regulation theory of individual differences and directions for future research.

Keywords: working memory capacity; attention control; fluid intelligence; mind-wandering; arousal; pupillometry

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Working memory and attention are two important systems that allow people to achieve the feats of human cognition. Individual differences in the ability to use such systems have been shown to predict a host of higher-order cognitive processes like the retrieval of information from long-term memory (Kane & Engle, 2000; Rosen & Engle, 1997; Unsworth et al., 2013, 2014; Unsworth & Engle, 2007; Unsworth & Spillers, 2010), the ability to implement future-oriented intentions (Brewer, Knight, Marsh, & Unsworth, 2010; Rose, Rendell, McDaniel, Aberle, & Kliegel, 2010; Smith & Bayen, 2005), the ability to read and recall information (Daneman & Carpenter, 1980; McVay & Kane, 2012b; Unsworth & McMillan, 2013), and the ability to reason with novel information (Engle, Tuholski, Laughlin, & Conway, 1999; Kyllonen & Christal, 1990; Unsworth et al., 2014; Unsworth & Spillers, 2010). Thus, a wealth of research has delved into the cognitive mechanisms underlying working memory capacity and attention control. One such mechanism is the ability to control attention under conditions of internal or external distraction.

Recently, one important observation is that people who have relatively low working memory capacity (WMC) and poor attention control (AC) tend to experience more frequent attentional lapses (Schmiedek, Oberauer, Wilhelm, Süß, & Wittmann, 2007; Unsworth et al., 2010; Unsworth & Robison, 2017a). Theoretically, these instances constitute moments when the individual's ongoing thoughts become captured by irrelevant internal or external information and the task goal is temporarily lost, leading to a diverse array of cognitive failures. In the laboratory, such lapses often manifest as slow and/or variable reaction times, errors, and poor memory performance (Adam, Mance, Fukuda, & Vogel, 2015; McVay & Kane, 2009, 2012a; Unsworth et al., 2010, 2020b). Corroborating these behavioral data, experience-sampling, both in and out of the lab, shows that people

with low WMC and poor AC typically self-report their thoughts deviating from an intended task or goal more often (Kane et al., 2007, 2016; Krimsky, Forster, Llabre, & Jha, 2017; McVay & Kane, 2009, 2012a, 2012b; Mrazek et al., 2012, 2012; Robison & Brewer, 2020; Robison, Gath, & Unsworth, 2017; Robison & Unsworth, 2015, 2018; Rummel & Boywitt, 2014; Unsworth & McMillan, 2013, 2014; Unsworth, McMillan, Brewer, & Spillers, 2012; Unsworth & Robison, 2016, 2017b; Unsworth et al., 2020b). This begs an important yet unanswered question: why do some people have a hard time maintaining goals in mind and resisting attentional failures like mind-wandering and distraction?

Unsworth and Robison (2017a) have proposed a theory that at least one major reason could be an inability to maintain a consistent level of arousal. Here we define arousal as the psychological state of readiness to respond to goal-related information. To an extent, arousal is governed by tonic activity in the locus coeruleus-norepinephrine (LC-NE) system. Slow, rhythmic firing (1 - 3 Hz) of neurons in the LC release NE into almost all areas of cortex, which allows these regions to function optimally. In addition to tonic firing, LC neurons exhibit brief (phasic) bursts of activity in response to goal-relevant stimuli (Berridge & Waterhouse, 2003; Samuels & Szabadi, 2008; Szabadi, 2013). Importantly, these modes of firing are interdependent. According to the Adaptive Gain Theory (Aston-Jones & Cohen, 2005), when tonic LC activity is particularly low, organisms are in a state of low alertness/drowsiness, and LC neurons show virtually no phasic responding. When tonic LC activity is particularly high, the organism is in a distractible state, and phasic responding occurs rather indiscriminately. At a moderate level of tonic LC activity, phasic responding is both large and task- or goal-specific. The phasic bursts only occur when a relevant stimulus has been perceived. Therefore, in instances where a tight coupling of attention to the environment is demanded, maintaining a moderate level of arousal is optimal.

Building on the Adaptive Gain Theory, Unsworth and Robison (2017a) proposed that

one possible mechanism driving variability in WMC and AC could be an inability to maintain a moderate level of arousal. When NE is not released in a consistent and appropriate manner, causing fluctuations in arousal between low, moderate, and high states, important neural networks like the fronto-parietal control network do not function optimally. Such breakdowns can lead to other major neural networks like the default mode network becoming active, generating internally-directed thoughts (i.e., mind-wandering) or attentional capture by irrelevant external stimuli (i.e., distraction). Such lapses can cause poor cognitive performance. Thus, the theory argues that dysregulation of arousal, caused by relative inconsistency of tonic LC activity, might explain why some people experience these lapses quite often and show low estimates of WMC and poor AC. In Figure 1, we illustrate what we mean when we characterize individuals as having regulated vs. dysregulated arousal. Two participants from the current dataset were selected for having high and low values of variability in pretrial pupil diameter, which we argue is a proxy for arousal (dys)regulation.

Because of its size and location, measuring LC activity in humans is quite difficult (although recent advances have been made using neuromelanin-sensitive magnetic resonance imaging; see Sun et al., 2020; Bachman et al., 2020; Ohtsuka et al., 2013). However, there is a rather tight temporal linkage between pupil diameter and the activity of LC neurons (Aston-Jones & Cohen, 2005; Joshi & Gold, 2020; Joshi, Li, Kalwani, & Gold, 2016; Varazzani, San-Galli, Gilardeau, & Bouret, 2015). Thus, we can estimate both tonic and phasic LC activity with pupil dilation. Leveraging this relation between LC firing rates and pupil size, researchers have started to demonstrate interindividual correlations between pupil measures and cognitive performance. Importantly, it has been demonstrated that trial-to-trial variability in pupil diameter correlates with lower estimates of WMC (Aminihajbashi, Hagen, Andreassen, Laeng, & Espeseth, 2020; Robison & Brewer, 2020; Robison & Unsworth, 2019; Unsworth & Robison, 2015, 2017b), poorer AC (Madore et al., 2020; Unsworth & Robison, 2017b), poorer long-term memory (Madore et

al., 2020), and more self-reported instances of TUTs (Robison & Brewer, 2020; Unsworth & Robison, 2017b). These data are consistent with the proposition that one aspect of low cognitive ability could be an inability to maintain a moderate level of arousal.

Along these same lines, Tsukahara, Harrison, and Engle (2016) have showed a positive correlation between measures of fluid intelligence and resting pupil size (see also Tsukahara & Engle, 2021, 2020; but see Aminihaibashi et al., 2020, who fail to find such a correlation). Tsukahara et al. argue that stronger functional connectivity in the default mode and executive-attention networks of the brain, driven by neuromodulation from the LC, can lead to differences in higher-order cognitive abilities like gF. This theory is very much in line with the arousal-regulation hypothesis proposed by Unsworth and Robison (2017a), and introduces an intriguing possibility: perhaps one general source of variation underlying individual differences in goal-directed cognition (attention, memory, reasoning) is the relative ability to regulate arousal. In the present study, we address this possibility by measuring arousal with pupil diameter and administering a battery of working memory, attention, and fluid reasoning tasks to a large sample of participants. Additionally, we included thought probes in some of the tasks to measure a general tendency to experience task-unrelated thoughts (TUTs) during such tasks.

The current study builds on prior work examining individual differences in pupillary measures and cognitive abilities. It merges the methods of studies that have assessed correlations between pupillary measures and cognitive performance within a task (e.g., Aminihaibashi et al., 2020; Madore et al., 2020; Robison & Unsworth, 2019; Unsworth & Robison, 2015), those that have examined correlations between cognitive abilities and resting-state pupil diameter (Aminihaibashi, Hagen, Foldal, Laeng, & Espeseth, 2019; Tsukahara & Engle, 2020, 2021; Tsukahara et al., 2016; Unsworth et al., 2020a; Unsworth, Robison, & Miller, 2019), and those that have used latent-variable modeling to assess arousal regulation at the construct level (Robison & Brewer, 2020; Unsworth & Robison,

2017b). It extends the latent-variable studies to include a factor for gF, which two prior studies were lacking (Robison & Brewer, 2020; Unsworth & Robison, 2017b) and it adds a measure of resting-state pupil diameter, which these two studies were also lacking.

Hypotheses

The arousal regulation hypothesis makes several specific predictions. First, it predicts that people who show more trial-to-trial variability in arousal will report more instances of TUT (i.e., mind-wandering, distraction, absentmindedness). Second, it predicts that participants with dysregulated arousal will tend to show poorer AC and lower WMC. A novel hypothesis in the present study is that arousal dysregulation will also predict lower gF, as it has previously been argued that individual differences in WMC and AC account for large portions of variance in gF. Thus, we hypothesize that one physiological mechanism that seems to underlie individual differences in working memory and attention might also underlie individual differences in higher-order cognition. Finally, we specifically hypothesize that any relation between arousal dysregulation and cognitive ability will be driven by the tendency to experience TUTs. As described earlier, we believe TUT is one important behavioral manifestation of arousal dysregulation, and thus should explain a large portion of the relations between cognitive abilities and arousal regulation. Thus, in addition to examining latent correlations among these factors, we specify several regression models to look at the mediated effects of arousal regulation on cognitive abilities after accounting for shared variance with TUT.

Method

We report how we determined our sample size, all data exclusions (if any), all manipulations, and all measures in the study.

Participants and procedure

A sample of 254 participants completed the study in exchange for partial course credit ($M_{age} = 19.31$, $SD = 2.10$, range: 18 - 46; 158 men, 95 women, 1 did not report gender). Our goal was to collect data from as many participants as possible, with a minimum viable sample size of 200 and using the end of an academic semester as our stopping rule for data collection. Sessions lasted 2 hours. Participants first provided informed consent, then completed a brief demographics questionnaire. They then completed the pre-experimental/baseline pupil measurement and a measurement of the pupillary light reflex (not analyzed or reported here). Then, they completed the following tasks, listed in order of completion: Operation Span (Unsworth, Heitz, Schrock, & Engle, 2005), the Psychomotor Vigilance Task (Dinges & Powell, 1985), the Raven Advanced Progressive Matrices (Raven, Raven, & Court, 1962), Symmetry Span (Unsworth, Redick, Heitz, Broadway, & Engle, 2009), a colored-squares change-detection task (Luck & Vogel, 1997), the antisaccade task (Kane, Bleckley, Conway, & Engle, 2001), letter sets (Ekstrom, Dermen, & Harman, 1976), the Sustained Attention to Response Task (Robertson, Manly, Andrade, Baddeley, & Yiend, 1997), Reading Span (Unsworth et al., 2009), and number series (Thurstone, 1938). The achieved sample sizes for each task are listed in Table 1. Relatively fewer participants completed the Reading Span and number series tasks because these came at the end of the experimental session. Once participants had been in the session for 2 hours, we allowed them to leave. Some participants took relatively longer on the tasks, leaving less time for the tasks at the end of the session, and some arrived to the session late. The experimental protocol was approved by the Institutional Review Board of Arizona State University.

Tasks

Operation span. In this task, participants solved a series of math operations while trying to remember a set of unrelated letters (Unsworth et al., 2005). Participants were

required to solve a math operation, and after solving the operation, they were presented with a letter for 1 s. Immediately after the letter was presented the next operation was presented. At recall participants were asked to recall letters from the current set in the correct order by clicking on the appropriate letters. For all of the span measures, items were scored correct if the item was recalled correctly from the current list in the correct serial position. Participants were given practice on the operations and letter recall tasks only, as well as two practice lists of the complex, combined task. List length varied randomly from three to seven items, and there were two lists of each length for a total possible score of 50. The score was total number of correctly recalled items in the correct serial position. The task took about 12 min to complete.

Symmetry span. Participants recalled sequences of red squares within a matrix while performing a symmetry-judgment task (Unsworth et al., 2009). In the symmetry-judgment task, participants were shown an 8 X 8 matrix with some squares filled in black. Participants decided whether the design was symmetrical about its vertical axis. The pattern was symmetrical half of the time. Immediately after determining whether the pattern was symmetrical, participants were presented with a 4 X 4 matrix with one of the cells filled in red for 650 ms. At recall, participants recalled the sequence of red-square locations by clicking on the cells of an empty matrix. Participants were given practice on the symmetry-judgment and square recall task as well as two practice lists of the combined task. List length varied randomly from two to five items, and there were two lists of each length for a total possible score of 28. The task took about 10 min to complete.

Reading span. While trying to remember an unrelated set of letters, participants were required to read a sentence and indicated whether or not it made sense (Unsworth et al., 2009). Half of the sentences made sense, while the other half did not. Nonsense sentences were created by changing one word in an otherwise normal sentence. After participants gave their response, they were presented with a letter for 1 s. At recall, participants were asked to recall letters from the current set in the correct order by clicking

on the appropriate letters. Participants were given practice on the sentence judgment task and the letter recall task, as well as two practice lists of the combined task. List length varied randomly from three to seven items, and there were two lists of each length for a total possible score of 50. We used the same scoring procedure as we used in the operation span and symmetry span tasks. The task took about 12 min to complete.

Colored-squares change detection. Each trial started with a black fixation cross against a grey background (RGB: 122, 122, 122) at the center of the screen for 1 s. Then, a set of 2, 4, or 6, colored squares appeared in random locations around the screen for 250 ms, with the one restriction being that items did not touch or overlap. The colors of items were sampled from a list of 9 discrete colors (red [255, 0, 0], blue [0, 0, 255], black [255, 255, 255], green [0, 255, 0], yellow [255, 255, 0], orange [255, 128, 0], cyan [0, 255, 255], and pink [255, 255, 255]). Colors did not repeat within a trial. After a 4-s delay, the items reappeared, and one item had a black circle around it. The participant’s task was to determine whether that item was the same color or a different color than it was on the initial presentation of the array. Participants indicated their response by pressing a key marked S for same or D for different. Trials were separated into 5, 6, 7, or 8-trial “blocks” (104 total trials), at the end of which a thought probe appeared (16 total probes). The change-detection task was included because it produces stereotypical patterns of pupillary measures (Robison & Brewer, 2020; Unsworth & Robison, 2015, 2018). The dependent variable from this task was a measure of capacity (k , computed using the formula [hit rate - false alarm rate]*[set size]). K was computed for each set size separately, then averaged across set sizes.

Antisaccade. On this task, participants had to identify the identity of a letter presented very briefly in their periphery. Each trial began with three cyan (RGB: 0, 255, 255) asterisks (***) centered on the screen against a black background. After a random amount of time ranging from 200 to 1,800 ms, a cyan equal sign (=) flashed either on the right or left side of the screen for 250 ms. Then, a cyan letter (B, P, or R) flashed on the

opposite side of the screen for 100 ms, followed by a letter mask (H) for 50 ms, then the number 8 until the participant made their response using three keys labeled B, P, and R (the 4, 5, and 6 keys on the number pad.) Trials were separated by a 400-ms blank screen. Participants completed 10 trials of response mapping (target letter appeared at the center of the screen), 10 trials of prosaccade (letter appeared on same side as flashing cue), and 10 practice antisaccade trials. Participants then completed 60 antisaccade trials which were scored for accuracy. The dependent variable was the proportion of correctly-identified letters on these trials.

Sustained Attention to Response Task (SART). On each trial, a single digit (1 - 9) appeared at the center of the screen. Participants were instructed to respond as quickly as possible to any digit other than the number 3 by pressing the spacebar. Target digits (go trials) comprised 89% of trials, whereas non-targets (no-go trials) comprised the remaining 11%. The digits appeared in black text (size 32 Arial font) on a grey background (RGB: 122, 122, 122) for 250 ms and were separated by a 1,750-ms mask (a capital X). Participants completed a practice block of 30 trials, then 450 trials. Trials were divided into blocks of 15, 30, or 45 trials (15 blocks total), at the end of which a thought probe appeared. The dependent variable and the standard deviation of response time (RT SD) on go trials.

Psychomotor vigilance task (PVT). Each trial started with a row of four black fixation crosses (+++++) against a grey background (RGB: 122, 122, 122). The fixation screen lasted 2 s. Then, a row of zeros appeared at the center of the screen (0.000). After a random time interval sampled uniformly from 2 to 10 s (in 500-ms increments), the zeros began “counting” like a stopwatch. The participant’s task was to press the spacebar as quickly as possible when they noticed that happen. After the participant pressed the spacebar, the timer stopped counting and showed their reaction time for that trial for 1 s (e.g., 0.356). After a 1-s blank intertrial interval, the next trial began. Trials were separated into 4 “blocks” of 4, 5, 6, or 7 trials, at the end of which a thought probe

appeared. Thus there were 88 total trials and 16 thought probes. We trimmed RTs outside 200 and 3000 ms. False alarm trials (key presses before the timer started counting) were also discarded. The dependent variable was the average of each participants slowest quintile of trials. The slowest quintile of trials is used as the dependent measure to replicate prior studies using the PVT in latent variable investigations of AC (Robison et al., 2017; Unsworth & McMillan, 2014; Unsworth et al., 2010), as well as other studies that have shown that the slowest response times in simple and choice reaction time tasks correlate most strongly with measures of WMC and gF (e.g., Schmiedek et al., 2007).

Raven Advanced Progressive Matrices. On each trial, participants were presented with a 3 x 3 matrix. The bottom-right corner of each matrix was missing. From a set of 8 possible options, participants were instructed to select the option that best completed an implicit pattern in the matrix. Participants were given a maximum of 10 minutes to complete the 18 odd items. The dependent variable was the total number of correct items.

Number series. Participants were presented with a sequence of 5 digits. From a set of 5 possible options, participants were instructed to select the number that best continued an implicit pattern in the sequence. Participants were given a maximum of 4.5 min to complete 15 items. The dependent variable was the number of correctly-selected items.

Letter sets. Participants were presented with a set of 4-letter sets. From those sets, participants had to select the set of letters that did not match the pattern present in the remaining sets. Participants had a maximum of 5 min to complete 20 items. The dependent variable was the number of correctly-selected items.

Thought probes. During the instructions to the PVT, SART, and change-detection tasks, we instructed participants, “Periodically, the computer will ask you what you are thinking about. You will see a screen that says: What were you thinking about in the few seconds preceding this screen? 1) I was focused on the current task, 2) I

was thinking about my performance on the task, 3) I was distracted by sights/sounds in my environment, 4) I was thinking about things unrelated to the task (e.g., daydreaming), 5) My mind was blank. When you see this screen, press the key that best describes your preceding thoughts.” On the actual probe screens, participants just saw the question, “What were you thinking about in the few seconds preceding this screen?” with the 5 response options. Participants pressed the corresponding number key to make their response, and the task resumed. We scored response 1 as on-task, response 2 as task-related interference, response 3 as external distraction, response 4 as mind-wandering, and response 5 as mind-blanking. We scored responses 3-5 as task-unrelated thoughts (TUTs). We used TUT rates (TUTs/total probes) for the PVT and change-detection tasks as an individual difference in the latent variable modeling. Unfortunately due to a programming error, responses to the thought probes were not properly recorded for the SART, and we were not able to use these data.

Pupillometry

We recorded pupil data during the SART, PVT, and change-detection tasks. Pupil data were collected via GazePoint GP3 eye-trackers. Prior to beginning each task, the researcher verified the eye-tracker was accurately reading the participant’s eyes with the GazePoint Control program. The eye-trackers sampled at 60 Hz and collected pupil diameter and gaze position from both eyes. We used the pupil diameter of the right eye for all analyses. We performed several procedures to ensure clean data. First, we filtered out any measurements that were outside a reasonable range (< 2 mm or > 8 mm). Then, we eliminated any “islands” in the data - instances where the same value was recorded consecutively for at least 100 ms (which for a measurement on the magnitude of hundreds of millimeters, is extremely unlikely). These samples were excluded from the analysis. Any participant who had more than 40% of their data missing for a particular task was excluded from analyses for that task. For the PVT, we used the mean pupil diameter over

the 2-s fixation screen as our pretrial pupil diameter measurement. For the SART, because the trial began with the onset of a digit rather than a fixation screen or mask, we used the mean pupil diameter over the last 500 ms of the preceding trial as our measure of pretrial pupil diameter. For the change-detection task, we computed the average pupil diameter over the 1-s fixation screen on each trial as our measure of pretrial pupil diameter. Then, we computed the mean, standard deviation, and coefficient of variation (CoV) of this measure across trials for each task. For estimates of reliability we used the split-half correlation between odd and even trials with the Spearman-Brown split-half correction.

Pre-experimental baseline measure. At the beginning of the session, participants first completed a baseline eye measurement. They were instructed to fixate on a central black fixation mark (+) presented against a grey background. Participants were told to keep their eyes focused on the fixation mark as much as possible, but that they could blink as needed. From this measure we extracted several dependent variables. First, we computed mean baseline pupil diameter as the average of all samples over the three-minute window. Then, we computed the standard deviation and coefficient of variation of all samples over the three-minute window. Samples were collected at 150 Hz, so there were roughly 27,000 samples in this window. To compute reliability, we segmented the data into three one-minute epochs and computed each of those three measures (mean, SD, CoV) within the three epochs. Then, we computed a Cronbach's α on these three measures. These measures were included in an attempt to replicate recent findings that resting/baseline pupil diameter correlates with working memory capacity and fluid intelligence (Aminihajibashi et al., 2019; Tsukahara & Engle, 2021; Tsukahara et al., 2016).

Data analysis

We used R software (R Core Team, 2017) for all our analyses. We used the *tidyverse* (Wickham, 2017) and *zoo* (Zeileis & Grothendieck, 2005) package to re-code, clean, and filter data, the *lavaan* (Rosseel, 2012) package to fit latent variable models, the *data.table*

(Dowle & Srinivasan, 2018) package to quickly aggregate data, the *psych* (Revelle, 2018) package for descriptive statistics, and the *papaja* (Aust & Barth, 2018) package to write the manuscript in R Markdown. All dependent variables were screened for outliers by eliminating any data point that fell outside ± 3 standard deviations of the mean. For all tasks other than the complex span tasks, we used the correlation between odd and even trials and the Spearman-Brown split-half correlation correction as an estimate of reliability. For the complex-span tasks, we used the Cronbach's α on accuracy by set size. All data and analysis scripts can be found on the Open Science Framework at the following url: <https://osf.io/db8qh/>

Results

Descriptive statistics for the behavioral measures are listed in Table 1. Almost all measures showed values for skewness and kurtosis in the acceptable ranges ($|\text{skew}| < 2$, $|\text{kurtosis}| < 4$; Kline, 2015), and most measures showed moderate to high reliabilities. Average accuracy and reliability for the antisaccade task were lower than is typically observed. It should be noted that this task was re-programmed into new software and adapted for use in the present study. Thus, minor changes across programs could have affected average accuracy. However, as will be seen with the individual-differences analyses, this did not appear to impact the rank-ordering of individuals, and in turn the degree to which the antisaccade measure correlated with the other AC measures. The slowest 20% of trials from PVT had the highest values of skewness and kurtosis. Inspection of the data revealed three participants whose values were more than 2 standard deviations above the mean. Our outlier threshold was 3 standard deviations outside the mean. We verified that the pattern of results did not systematically differ when including or excluding these participants, so we retained them for the analysis.

Responses to the thought probes in the PVT and change-detection tasks are plotted in Figure 2. Paired-samples *t*-tests compared thought probe responses across the two tasks.

Participants reported being on-task significantly more often in the change-detection task ($t(254) = 8.53, p < .001, d = 0.55$) and thus fewer TUTs ($t(254) = -4.75, p < .001, d = 0.29$). Specifically, participants reported more mind-wandering during the PVT ($t(254) = -4.96, p < .001, d = 0.30$), but there was no difference in external distraction ($t(254) = -1.21, p = .227, d = 0.09$) or mind-blanking ($t(254) = -0.76, p = .445, d = 0.06$).

Participants also reported less task-related interference during change-detection compared to the PVT ($t(254) = -5.67, p < .001, d = 0.42$). Despite these between-task effects, reports were correlated across tasks. Participants who reported more TUTs during the PVT also reported more TUTs during the change-detection task ($r(253) = 0.55, p < .001$).

The next set of analyses examined individual differences in the cognitive ability (WMC, AC, gF) measures and TUT rates using latent variable modeling. Table 2 lists zero-order correlations among measures used in the latent variable models. We specified several different latent models and compared these models before deciding on a measurement model. In Model 1, we allowed all the WMC and AC (i.e., *executive attention*) tasks (operation span, symmetry span, reading span, change-detection, antisaccade, PVT, and SART) to load onto a factor, the gF tasks (Raven, number series, and letter sets) to load onto a factor, and TUT rates from PVT and change-detection to load onto a factor. This three-factor model did not fit the data well (see Table 3 for fit statistics for all models). In Model 2, the WMC tasks loaded onto a factor, the AC and gF tasks loaded onto a factor, and the TUT reports loaded onto a factor. This three-factor model also did not fit the data well. Therefore, in Model 3 we allowed the complex span WMC tasks to load onto a factor, the AC tasks to load onto a factor, the gF tasks to load onto a factor, and TUT reports to load onto a factor. We allowed k estimates from the change-detection task to load onto both the WMC and AC factors. This model fit the data well, and significantly better than the first two models. Inspection of this model revealed that the change-detection k scores significantly loaded onto the AC model (loading = 0.59) but not the WMC factor (loading = -.03). Therefore, in Model 5, we only allowed k

estimates to load onto the AC factor.¹ Finally, inspection of modification indices revealed a large residual correlation between k estimates and TUT reports from the change-detection tasks. Therefore, we allowed the error variances from these two measures to correlate. This final model is shown in Figure 3.

The cognitive abilities correlated in a manner consistent with prior research (Draheim, Tsukahara, Martin, Mashburn, & Engle, 2020; Shipstead, Lindsey, Marshall, & Engle, 2014; Tsukahara et al., 2020; Unsworth et al., 2014; Unsworth & McMillan, 2014; Unsworth & Spillers, 2010). Specifically, participants with higher WMC estimates also tended to show better AC and higher gF, and participants with better AC tended to show higher gF. Further, TUTs negatively correlated with all three cognitive abilities. That is, participants who reported more TUTs tended to have lower WMC estimates, lower AC, and lower gF. This pattern of results is also consistent with prior research (Kane et al., 2016; McVay & Kane, 2012a; Robison et al., 2020; Robison & Unsworth, 2015; Unsworth & McMillan, 2014).

The next set of analyses examined pupillary measures drawn from the pre-experimental baseline measurement. The primary purpose of this analysis was to replicate Tsukahara et al. (2016)'s finding of a positive association between resting pupil diameter, WMC, and gF. Table 4 lists descriptive statistics for the measures of average and intraindividual variability (SD and CoV) in baseline pupil diameter. The measures each showed a fair amount of interindividual variability as well as reliability, which are important for investigating individual differences. Next, we examined how these measures correlated with the cognitive factors specified above (i.e., WMC, AC, gF, and TUT). Table 5 shows the correlations. Correlations between the baseline pupil measures and the cognitive abilities were largely weak and non-significant, but there were significant

¹ This is consistent with recent work showing that change-detection tasks sometimes correlate more highly with AC measures than with complex span WMC measures (Martin et al., 2021)

negative correlations between variability in resting pupil diameter (SD and CoV), AC, and gF. Thus, people who tended to show more fluctuations in pupil diameter, even in the absence of a task, tended to then show lower AC and gF. We did not replicate Tsukahara et al. (2016)’s and Tsukahara and Engle (2021)’s findings of positive correlations between WMC and gF and resting pupil diameter, nor Aminihaajibashi et al. (2019)’s finding of a negative correlation between resting pupil variability and WMC.

Next, we examined within-task pupillary measures and their correlations with cognitive abilities and TUTs. To do so, we specified two additional latent factors: one representing average arousal and one representing intraindividual variability in arousal. We used the mean pretrial pupil diameter from the PVT, SART, and change-detection tasks as measures of average arousal and we allowed these three measures to load onto an “average arousal” factor, and the CoV of pretrial pupil diameter from these same tasks to load onto an “arousal dysregulation” factor. Additionally, error variances for mean and CoV measures from the same task were allowed to correlate. The model fit the data well ($\chi^2(117) = 225.51$, CFI = 0.92, NNFI = 0.90, RMSEA = 0.06 [0.05, 0.07], SRMR = 0.07). The model is depicted visually in Figure 4, and Table 6 lists the correlations among the latent variables in the model. Only two correlations between cognitive factors and arousal factors were significant. The arousal dysregulation factor negatively correlated with AC and positively correlated with TUT. That is, participants who demonstrated more trial-to-trial variability in arousal tended to have lower AC and report more TUTs. The correlations between arousal dysregulation and WMC and between arousal dysregulation and gF were not significant (see Figure 5). Thus, we did not observe a significant direct association between arousal regulation and WMC, nor between arousal regulation and gF. Our next set of analyses examined the shared and unique influences of arousal dysregulation and TUT on the cognitive abilities (WMC, AC, and gF) in a set of regression models.

In the Introduction, we hypothesized that any covariance between cognitive abilities

and arousal dysregulation would be accounted for by shared variance with TUT. To partition variance, we saved factor scores for each participant and submitted these scores to a sequence of linear models with arousal dysregulation as a sole predictor, TUT as a sole predictor, and arousal dysregulation and TUT both as predictors. The results of these analyses are shown in Figure 6. Arousal dysregulation and TUT accounted for 37% of the variance in AC, with 25% uniquely attributable to TUT, 3% uniquely attributable to arousal dysregulation, and 9% attributable to the shared variance between TUT and arousal dysregulation. Thus, even after accounting for TUT, there was still some shared variance between arousal dysregulation and AC. Arousal dysregulation and TUT accounted for 18% of the variance in WMC, 16% uniquely due to TUT and 2% due to a shared influence of between TUT and arousal dysregulation. Although this is consistent with our hypothesis that TUT would account for shared variance between arousal and cognition, the shared influence of TUT and arousal dysregulation accounted for only a small portion of variance in WMC. This pattern was very similar for gF. Arousal dysregulation and TUT accounted for 15% of the variance in gF, 13% uniquely attributable to TUT and 2% due to a shared influence of TUT and arousal dysregulation. Again, this pattern is consistent with our hypothesis, but only accounted for a small portion of variance in gF.

Discussion

The goal of the present study was to replicate prior work examining individual differences in arousal regulation, attention control (AC), and working memory capacity (WMC), and extend that methodology to investigate how arousal regulation might account for individual differences in fluid intelligence (gF). To do so, we measured pupil diameter during a set of tasks to measure both average arousal levels and trial-to-trial fluctuations in arousal. More trial-to-trial variability in pupil diameter, we argue, reflects dysregulation of arousal, which has been shown to correlate with individual differences in WMC, AC, and the tendency to experience task-unrelated thoughts (TUTs; Unsworth & Robison, 2015,

2017b; Aminihaibashi et al., 2020; Madore et al., 2020; Robison & Brewer, 2020). We measured arousal both before participants completed any tasks and while participants completed three tasks. During a 2-hour session, participants completed a battery of working memory, attention, and fluid reasoning tasks. Two of the tasks also had thought probes embedded in them for measurement of TUTs (e.g., mind-wandering, external distraction).

First, we replicated a rather consistent pattern of results that participants with higher WMC and stronger AC have higher gF estimates. Further, we replicated the pattern that participants with higher WMC and AC tend to report fewer TUTs. Relatively fewer studies have investigated the correlation between gF and TUTs, but we observed a negative correlation in the present study similar to prior work (Unsworth & McMillan, 2014, 2017). That is, participants who performed better on the gF tasks tended to report fewer TUTs during the two tasks that included thought probes. Thus, our behavioral data were largely consistent with prior work examining these cognitive abilities.

Second, we did not replicate Tsukahara et al.'s (2021; 2016) finding of positive correlations between resting pupil diameter and cognitive abilities, particularly with gF (see also Heitz, Schrock, Payne, & Engle, 2008). Our findings are consistent with a recent meta-analysis showing a null association between WMC and resting pupil diameter (Unsworth et al., 2020a). We do not believe this was due to a restriction of range, as our interindividual mean and standard deviation were very close to that observed by Tsukahara and Engle (2021) in the conditions under which they observed significant associations. We also do not believe the present study suffered from a lack of statistical power, as we would have been able to detect a correlation of .20 with 92% power ($\alpha = .05$) with the present sample size. Therefore, it is still yet unclear why significant associations between resting pupil size and cognitive abilities are sometimes observed, and others they are not. Future work is certainly necessary (see Tsukahara et al., 2021; Unsworth, Miller,

& Robison, 2021 for a recent discussion).

We did observe significant associations between variability in resting pupil diameter, AC, and gF. People who showed more fluctuations in resting pupil diameter during the pre-experimental measurement tended to exhibit lower AC and lower gF. However, there were not significant associations between resting pupil variability and WMC or TUT. Significant correlations between resting pupil variability and cognitive abilities have not been observed previously (Tsukahara & Engle, 2021; Tsukahara et al., 2016; Unsworth et al., 2019). Therefore, these correlations beg replication.

Third, we examined associations among the cognitive abilities (WMC, AC, gF), tendencies toward TUT, and both average arousal and arousal regulation from trial-to-trial pupil measures taken during three tasks. Average arousal did not correlate with any of the cognitive factors. Arousal regulation only significantly correlated with AC and the tendency to report TUT. Correlations between arousal regulation and WMC and between arousal regulation and gF were rather weak and non-significant. These data indicate that arousal regulation is a potentially important correlate of AC and the tendency to experience attentional lapses. However, the associations between arousal dysregulation and gF and between arousal dysregulation and WMC were much weaker. Finally, we assessed shared and unique associations between arousal regulation, TUT, AC, WMC, and gF. We did so by specifying several regression models in which arousal dysregulation and TUT were set as predictors of AC, WMC, and gF, respectively. These models were specified to test our hypothesis that the association between arousal regulation and cognitive ability is at least partially because arousal dysregulation causes fluctuations in attentional state. This is a pattern that would be predicted by the Adaptive Gain Theory of LC-NE functioning (Aston-Jones & Cohen, 2005) and the arousal regulation theory of individual differences (Unsworth & Robison, 2017a). Arousal dysregulation had a unique and shared effect on AC. So TUT did not completely mediate the relation between arousal dysregulation and

AC. This suggests there is covariance between arousal regulations and AC that is not entirely attributable to subjective attentional disengagement. This will be an interesting area for future research. Although the analyses on WMC and gF were consistent with our hypothesis, as all covariance between arousal dysregulation and WMC/gF was attributable to its shared variance with TUT, the portions of variance accounted for by this confluence were quite small (2% gF and 0% for WMC).

Although there were modest correlations between TUT and the cognitive abilities measured here (AC, WMC, and gF), the present results reinforce the idea that the subjective experience of attentional lapses is not isomorphic with objective attentional indicators (e.g., errors, slow RTs). Thus, there are some people who do well on the tasks who still report high proportions of TUTs, whereas there are others who do relatively poorly on the tasks who nonetheless do not report high levels of TUT. This distinction is thus important, because we cannot safely assume that people who do poorly on tasks are just experiencing TUT, and vice versa.

Limitations

It is worth mentioning some important features of the present data that may be limiting factors. First, the change-detection pupillary measures had the strongest correlations with both performance and TUT. Thus, it is possible that the change-detection task is the “glue” holding the model together. Removing all measures from the change-detection task does several things. First, it prevents us from specifying a factor for TUTs, as we would then only have one measure with TUT reports, because of the programming error in SART. Second, it reduces our number of manifests for the CoV and Mean pupil factors down to two measures per factor. When removing all change-detection-related measures (mean pretrial, CoV pretrial, TUT, and k estimates), the model does not converge upon a solution when allowed to freely load. If instead we specify the loadings for which there are only two manifests (mean pretrial, CoV pretrial) to

be equal, and we specify the TUT factor to be a manifest of PVT TUT only, the correlations do indeed drop. For example, the correlation between CoV factor and AC factor drops from -0.29 to -0.20 (n.s.), and the correlation between TUT and CoV drops from 0.25 to 0.03. This is due to the very small correlation between PVT TUTs and PVT pretrial pupil CoV.

This is indeed problematic, for both the model and for the theory. So to see whether this correlation should be expected to be null, or perhaps this sample is showing just a particularly low correlation, we examined the zero-order correlation between pretrial pupil variability and PVT in several other datasets. The first was reported by Unsworth and Robison (2017b). There, they report a zero-order correlation of 0.21 between PVT TUT and PVT pretrial pupil variability (*SD*). In two unpublished datasets, the zero-order correlations are 0.08 ($N = 133$) and 0.17 ($N = 356$). Therefore, the correlation is modest, on aggregate, but the observed correlation in the present dataset is the lowest that has been observed in four different studies.

Considering all of this, we decided to retain the model structure with the change-detection tasks included. Although the PVT measures show limited interrelatedness, we still believe there is value in estimating the relations at a factor level, allowing for an assessment of the relations among sources of shared variance, despite some admittedly low zero-order correlations. The goal of specifying these constructs at the factor level was to correct for the fact that occasionally, relations are not strong on the task- or zero-order level, and latent variable modeling allows for an assessment of construct-level relations.

Future directions

There are three ways of interpreting this set of results, each of which opens questions for future research. The first interpretation is that arousal dysregulation is a

domain-general individual difference, since it accounts for a significant portion of variance in both AC and tendencies toward TUT, which we know have implications for other cognitive processes. Further, arousal dysregulation was indirectly related gF via shared variance with TUT. However, arousal dysregulation did not significantly correlate with WMC or gF factors. Therefore, a second interpretation of these data is that arousal dysregulation is an important underlying factor influencing individual differences in AC, but less important for WMC and gF. This raises an even more pressing question. If indeed attention control is the linchpin that unifies goal-directed cognition (specifically WMC and gF), as has been argued (Burgoyne & Engle, 2020; Engle, 2002, 2018; Engle et al., 1999), why didn't arousal regulation correlate with WMC and gF? People with relatively dysregulated arousal are demonstrating the behavioral hallmarks of poor AC: slow and variable RTs and failures to override prepotent responses. Additionally, they are self-reporting more instances of TUTs. Further, people with low estimates of AC and high TUT rates tended to have low WMC and gF. This suggests that perhaps, the set of processes shared among AC, WMC, and gF is separable than the set of processes shared among AC, TUT, and arousal regulation. It should be noted that there *is* evidence for a correlation between arousal dysregulation and WMC outside the present study. Unsworth and Robison (2015) observed a correlation between k estimates colored-squares change-detection task and arousal regulation, Robison and Unsworth (2019) observed a correlation with a colored-squares discrete whole-report task, Unsworth and Robison (2017b) observed a correlation with a factor comprising complex span measures, Robison and Brewer (2020) observed a correlation with a factor comprising three change-detection tasks (but not with a factor comprising complex span tasks), and Aminihaajibashi et al. (2020) observed a correlation with a letter-number sequencing task. Therefore, it would not be accurate to say WMC *never* correlates with arousal dysregulation, but it did not correlate in this study with our selected measures of WMC. This is the second study, to our knowledge, that has examined the correlation between trial-to-trial arousal variability

in association with gF. Aminihaibashi et al. (2020) did not observe a significant relation, and neither did we here.

A third interpretation of these data is that arousal regulation is not driven by a trait-level individual difference, but rather state-level differences present at the time of measurement. One aspect of studies examining the association between arousal regulation and factors like WMC and AC is that they often measure everything within a single laboratory session. Therefore, any psychological states that participants carry into the lab can permeate all measures. Thus, it could be the case the arousal regulation is a manifestation of a state variable, such as motivation, fatigue, or stress. In prior work, motivation has been shown to correlate with mind-wandering during attention-demanding tasks (Robison et al., 2020; Robison & Unsworth, 2015, 2018; Seli, Cheyne, Xu, Purdon, & Smilek, 2015; Seli, Wammes, Risko, & Smilek, 2016; Unsworth & McMillan, 2013; Unsworth et al., 2020b), and motivation has also correlated with performance on AC tasks (Robison et al., 2020; Robison & Unsworth, 2018; Unsworth et al., 2020b). It has also been shown that self-reported alertness correlates with both mind-wandering and performance on attention-demanding tasks (Robison et al., 2020; Robison & Unsworth, 2018; Unsworth et al., 2020b). Interestingly, such self-reports of motivation and alertness tend to correlate much weaker, or not at all, with complex span measures of WMC (Robison et al., 2020; Robison & Unsworth, 2018; Unsworth et al., 2020b), much in the same way arousal regulation correlated with AC and TUT in the present study, but much weaker or not at all with WMC and gF. Thus, it could be the case that the predictive power of arousal regulation is driven much more by state factors than trait factors. Aminihaibashi et al. (2020) make a similar argument given their findings. Specifically, they found a positive correlation between multiple-object tracking (MOT) performance and the magnitude of pupillary dilations while tracking those objects, particularly at high set sizes (e.g., 5 items at a time). Interestingly, neither these pupillary responses nor MOT performance correlated with measures of WMC or gF. Aminihaibashi et al. (2020) interpreted these

findings to mean that MOT relies on a separate set of resources that are not overlapping with those demanded by typical WMC and gF tasks. Or, that shared variance between pupillary responses and MOT performance could be due to something like task-specific effort expenditure/motivation. Again, this begs the question of how much interindividual variance in pupillary measures of arousal and effort are stable within an individual across situations and across tasks, and how much is due to task- and state-specific factors. Within individuals within a session, measures of arousal regulation are significantly intercorrelated (see Table 2). Therefore, arousal regulation was a stable individual difference within a session. However it is an open question whether arousal regulation will be a stable individual difference across sessions.²

The findings pave the way for a host of future directions which we plan to pursue. First, to our detriment, we did not have measures of state variables like motivation, fatigue, and stress in the present study. Therefore, we could not determine whether arousal regulation would correlate with such states. This is a much-needed area for future research. Second, we plan to assess the trait stability of arousal regulation across multiple measurements. That is, do people who show arousal dysregulation on one day of measurement also tend to show arousal dysregulation on a second day of measurement days, weeks, or even months apart? These data will help to answer the question of whether arousal regulation exerts a state-specific or trait-level influence on cognitive performance and task-unrelated thought. Finally, in future work we hope to examine the degree to which arousal regulation is manipulable via psychological or physiological intervention. If indeed it is manipulable, a rather straightforward prediction is that decreasing intraindividual variability in arousal should reduce task-unrelated thoughts and improve attention control. As such, measuring the effect of experimental manipulations on behavior, subjective state, and arousal together can provide more specific theorizing about how interventions affect

² We were in the midst of collecting such data when our lab operations ceased due to COVID-19. It is our intention to resume this research when it is safe to do so.

both the underlying physiological systems and the psychological processes they implement.

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Table 1
Descriptive statistics for cognitive ability measures

Measure	<i>N</i>	Mean	SD	Min	Max	Skew	Kurtosis	Reliability
Operation span	247	38.17	7.67	14.00	50.00	-0.80	0.36	0.78
Symmetry span	253	19.35	5.11	5.00	28.00	-0.56	-0.30	0.65
Reading span	181	32.47	10.83	0.00	50.00	-0.92	0.55	0.81
Change-detection k	250	1.94	0.95	-0.95	3.84	-0.52	0.16	0.81
Antisaccade	248	0.40	0.10	0.22	0.72	0.65	0.09	0.67
SART - RT SD	230	257.16	128.22	56.60	685.11	1.36	1.78	0.94
PVT	241	538.97	95.72	349.12	887.95	0.85	0.71	0.91
Raven	254	8.67	3.42	0.00	17.00	-0.08	-0.52	0.80
Number series	183	8.74	3.11	0.00	15.00	-0.37	-0.46	0.76
Letter sets	251	10.05	3.47	1.00	19.00	0.13	-0.44	0.74
Change-detection TUT	253	0.38	0.32	0.00	1.00	0.44	-1.05	–
PVT TUT	245	0.47	0.25	0.00	1.00	0.03	-0.64	–

Note. SART = Sustained Attention to Response Task, RTSD = standard deviation of reaction time, k = capacity estimate, PVT = psychomotor vigilance task. TUT = task-unrelated thought proportion.

Table 2

Zero-order correlations among measures used in latent variable modeling

	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.	15.	16.	17.	18.
1. Operation span	–																	
2. Symmetry span	.28*	–																
3. Reading span	.40*	.30*	–															
4. Change-detection k	.04	.22*	.26*	–														
5. Antisaccade	.04	.19*	.17*	.25*	–													
6. SART RT SD	-.02	-.26*	-.21*	-.36*	-.19*	–												
7. PVT	-.08	-.31*	-.09	-.25*	-.26*	.41*	–											
8. Raven	.14*	.27*	.20*	.29*	.35*	-.31*	-.22*	–										
9. Number series	.22*	.31*	.30*	.35*	.35*	-.35*	-.30*	.47*	–									
10. Letter sets	.26*	.31*	.41*	.31*	.32*	-.35*	-.24*	.39*	.56*	–								
11. PVT TUT	-.20*	-.10	-.10	-.18*	-.16*	.26*	.31*	-.05	-.16*	-.17*	–							
12. CD TUT	-.09	-.10	-.24*	-.43*	-.14*	.31*	.23*	-.16*	-.24*	-.19*	.58*	–						
13. PVT pupil M	.04	.03	.11	.09	-.02	-.03	-.09	.04	.07	.00	.04	-.06	–					
14. SART pupil M	-.02	-.02	-.02	.05	-.19*	.07	.07	-.09	-.03	-.05	.16*	-.02	.76*	–				
15. CD pupil M	.01	.09	.16*	.17*	-.07	-.11	-.12	.03	.04	.07	.01	-.13*	.81*	.75*	–			
16. PVT pupil CoV	.04	-.02	.03	-.12	-.04	.07	.23*	-.03	-.05	-.07	.05	.13*	-.10	-.06	-.07	–		
17. SART pupil CoV	.10	-.01	.04	.00	.08	.07	.05	.12	.01	.06	-.08	.06	-.22*	-.41*	-.25*	.41*	–	
18. CD pupil CoV	.08	-.03	-.09	-.29*	-.08	.24*	.22*	.04	-.18*	-.18*	.18*	.30*	.02	-.01	-.16*	.52*	.29*	–

Note. SART = Sustained Attention to Response Task, RT SD = standard deviation of reaction time, FA = false alarm rate, PVT = psychomotor vigilance task, CD = change-detection, TUT = task-unrelated thought proportion, M = mean, CoV = coefficient of variation. *correlation significant at $p < .05$.

Table 3

Model fit statistics for measurement models

Model	χ^2	df	CFI	NNFI	RMSEA	SRMR
Three-factor (ExAttn, gF, TUT)	139.23	52	0.86	0.82	0.08	0.06
Three-factor (WMC, AC/gF, TUT)	150.73	52	0.84	0.80	0.09	0.07
Four-factor (k on WMC and AC	109.09	48	0.90	0.86	0.07	0.05
Four-factor (k on AC only)	109.09	49	0.90	0.87	0.07	0.05
Four-factor (freed error variance)	84.24	48	0.94	0.92	0.05	0.05

Note. df = model degrees of freedom, CFI = confirmatory fit index, NNFI = non-formed fit index, RMSEA = root mean squared error of approximation, SRMR = standardized root mean residual

Table 4

Descriptive statistics for pre-experimental and pretrial pupil measures

	N	Mean	SD	Min	Max	Skew	Kurtosis	Reliability
Baseline pupil diameter - Mean	252	4.40	0.79	2.54	6.66	0.30	-0.41	0.97
Baseline pupil diameter - SD	251	0.50	0.16	0.04	1.07	0.55	1.40	0.86
Baseline pupil diameter - CoV	251	0.11	0.03	0.01	0.21	0.32	1.10	0.80
PVT pretrial pupil diameter - Mean	245	4.20	0.67	2.94	6.31	0.37	-0.22	0.99
PVT pretrial pupil diameter - CoV	245	0.12	0.04	0.02	0.37	2.01	7.68	0.96
SART pretrial pupil diameter - Mean	231	4.18	0.74	2.48	6.59	0.36	-0.09	0.99
SART pretrial pupil diameter - CoV	231	0.14	0.05	0.05	0.36	1.16	2.85	0.98
Change-detection pretrial pupil diameter - Mean	252	4.12	0.68	2.53	5.98	0.41	-0.20	0.99
Change-detection pretrial pupil diameter - CoV	252	0.13	0.05	0.00	0.36	1.11	2.14	0.96

Note. SD = standard deviation, CoV = coefficient of variation, PVT = Psychomotor Vigilance Task, SART = Sustained Attention to Response Task

Table 5

Correlations between pre-experimental baseline pupil measures and cognitive factors

	Mean	SD	CoV
Working memory capacity	0.12	0.08	0.04
Attention control	-0.10	-0.18*	-0.13
Fluid intelligence	-0.03	-0.16*	-0.15*
Task-unrelated thoughts	0.10	0.13	0.09

Note. WMC = working memory capacity, AC = attention control, gF = fluid intelligence, TUT = task-unrelated thoughts, M = mean, SD = standard deviation, CoV = coefficient of variation.

*correlation significant at $p < .05$.

Table 6
Correlations among cognitive factors and arousal factors

	1	2	3	4	5
1. Working memory capacity	–				
2. Attention control	0.51*	–			
3. Fluid intelligence	0.70*	0.79*	–		
4. Task-unrelated thoughts	-0.31*	-0.52*	-0.30*	–	
5. Average arousal	0.11	0.07	0.04	0.00	
6. Arousal dysregulation	0.04	-0.35*	-0.11	0.22*	-0.12

Note. CoV = coefficient of variation, latent correlation significant at
 * $p < .05$.

Figure 1. Pretrial pupil diameter data for two participants selected from the current dataset because they demonstrate relatively regulated arousal (left panel) and relatively dysregulated arousal (right panel). Data are from the psychomotor vigilance task. Dashed lines represent average pretrial pupil diameter for each participant.

Figure 2. Average response proportions to thought probes in the psychomotor vigilance task (PVT) and change-detection task. Participants reported being on-task more in the change-detection task. In the PVT, participants reported more mind-wandering, mind-blanking, and task-related interference. Error bars represent +/- one standard error.

Figure 3. Confirmatory factor analysis of measures of working memory capacity, attention control, fluid intelligence, and task-unrelated thoughts. Boxes represent measured (manifest) variables and ovals represent latent variables. All manifest variables loaded onto the hypothesized factors significantly, and all correlations among the latent variables were significant at $p < .05$.

Figure 4. Confirmatory factor analysis of measures of working memory capacity, attention control, fluid intelligence, and task-unrelated thoughts. Boxes represent measured (manifest) variables and ovals represent latent variables. All manifest variables loaded onto the hypothesized factors significantly. Solid lines indicate significant correlations at $p < .05$, dashed lines indicate non-significant paths.

Figure 5. Scatterplots of correlation between arousal dysregulation and a) attention control, b) working memory capacity, c) fluid intelligence, and d) task-unrelated thoughts. Values are factors scores from latent variable model.

Figure 6. a) Variance uniquely attributable to arousal dysregulation, uniquely attributable to task-unrelated thoughts, and jointly attributable to arousal dysregulation and task-unrelated thoughts in a) attention control (AC), b) working memory capacity (WMC), and fluid intelligence (gF).