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The relationship between sustained attention and parasympathetic functioning

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ABSTRACT

Sustained attention (SA) is an important cognitive ability that plays a crucial role in successful cognitive control. Resting vagally-mediated heart rate variability (vmHRV) has emerged as an informative index of parasympathetic nervous system activity and a sensitive correlate of individual differences in cognitive control. However, it is unclear how resting vmHRV is associated with individual differences in sustained attention. The primary aim of the current study was to assess if resting vmHRV was associated with individual differences in performance on a neuropsychological assessment of sustained attention. We further aimed to characterize the relationship between resting vmHRV and dispositional factors related to sustained attention, specifically attentional errors in daily life, self-regulation, mindfulness and media-multitasking. Based on previous work, we hypothesized higher resting vmHRV would be associated with better sustained attention across task-based and self-report measures. We did not find resting vmHRV to be significantly associated with performance measures on a task-based assessment of sustained attention. Further, resting vmHRV was not significantly associated with attention errors, self-regulation, mindfulness, or media-multitasking. This work stands to expand the current understanding between parasympathetic functioning, cognition, and behavior, investigating the unexplored domain of sustained attention and related dispositional factors.

1. Introduction

Sustained attention (SA) is the ability to maintain focus of attention and remain alert over an extended period (Esterman and Rothlein, 2019). The ability to sustain attention to a relevant task while inhibiting task-irrelevant thoughts and distractions is a crucial cognitive ability that underlies individual differences in executive functioning (deBettencourt et al., 2019) and memory (Madore et al., 2020). SA also plays a significant role in functional outcomes in academics (Steinmayr et al., 2010), social communication (Bennett Murphy et al., 2007), and driver safety (Yanko and Spalek, 2013). The importance of SA to cognitive functioning has led to a considerable amount of research on individual differences in SA (Esterman and Rothlein, 2019; Fortenbaugh et al., 2017b). Factors like age (Fortenbaugh et al., 2015), gender (Riley et al., 2016), neuropsychiatric distress (Esterman et al., 2019; Fortenbaugh et al., 2017a), and metabolic health (Wooten et al., 2019) have a considerable influence on SA.

To further understand individual differences in SA, researchers have started investigating differentiating aspects in parasympathetic nervous system functioning as a potentially influential factor (Siennicka et al., 2019; Spangler et al., 2018; Williams et al., 2016). Recent evidence suggests vagally-mediated heart rate variability (vmHRV) is a reliable

Abbreviations: BMI, body mass index; CV, coefficient of variation in reaction time; D', discrimination ability; GradCPT, gradual-onset continuous performance task; HF, absolute power of the high-frequency band (0.15–40 Hz); HRV, heart rate variability; IBIs, interbeat intervals; LF, absolute power of the low-frequency band (0.04–0.15 Hz); LF/HF ratio, ratio between LF-to-HF power; PNN50, percentage of successive RR intervals that differ by >50 ms; RMSSD, root mean square of the successive differences between normal heartbeats; RR, interbeat interval between successive heartbeats; RT, reaction time; SA, sustained attention; SDNN, standard deviation of interbeat interval after artifact removal; vmHRV, vagally-mediated heart rate variability.

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proxy for parasympathetic functioning (Shaffer and Ginsberg, 2017). High resting vmHRV is a relatively stable measure linked to greater cognitive control (Forte et al., 2019). Two theoretical frameworks have been instrumental in understanding the link between vmHRV and cognitive control: the Neurovisceral Integration Model (Thayer and Lane, 2009) and Polyvagal theory (Porges, 2009). The Neurovisceral Integration Model proposed resting vmHRV reflects the brain's baseline ability to integrate information and provide adaptive regulation that allows for flexible behavioral control (Thayer and Lane, 2009). The Neurovisceral Integration Model has been foundational in understanding the link between resting vmHRV, cognition, and emotional regulation; inspiring research in the fields of neuropsychology (Forte et al., 2019), neuropsychiatry (Thayer and Lane, 2000), and neuroimaging (Thayer et al., 2012) that have validated and extended the theory. Previous work has documented the association between vmHRV and selective attention (Park et al., 2013), and the role of vmHRV in modulating underlying perceptual processing in attention (Park and Thayer, 2014). Recently, several studies have explored the underlying relationship between resting vmHRV and the domain of SA specifically. Higher resting vmHRV was associated with more consistent performance on the D2 test of attention, despite not being associated with overall performance (Siennicka et al., 2019). In a study that utilized a modified flanker task, higher resting vmHRV was associated with lower reaction time variability, a measure of attention stability, after controlling for accuracy and mean reaction time (Williams et al., 2016). In another study, higher resting vmHRV was associated with lower reaction time variability on the Stroop task, an assessment of inhibition (Spangler et al., 2018). These studies suggest higher resting vmHRV may represent a greater baseline ability to sustain attention. Yet, utilizing a variety of tasks designed to assess attention and executive functioning, not SA directly, limits our ability to fully characterize SA, leaving important performance measures unexplored.

Predating the Neurovisceral Integration Model, Polyvagal theory focuses on the evolution of the autonomic nervous system for adaptive self-regulation and social communication (Porges, 1972, 2009; Walter and Porges, 1976). Notably, the polyvagal theory emphasizes the evolutionary benefits to survival of an adaptive autonomic nervous system. Polyvagal theory is more controversial than the Neurovisceral Integration Model based on the physiological and biological claims regarding two distinct brainstem centers with unique evolutionary origins and roles in parasympathetic control (Berntson et al., 2007). Under polyvagal theory, increased vagal influence of the heart is thought to be optimal for social functioning, while vagal withdrawal (decline in vmHRV during testing relative to rest) is optimal in situations requiring a fight-or-flight response. In theorizing the relationship between vmHRV and SA, Porges (1992) proposed maintaining a state of SA requires significant disruptions to homeostatic mechanisms to mobilize attentional resources. Several studies have demonstrated reduced vagal tone during sustained attention, finding that measures of vmHRV are uniquely sensitive to SA demands, above and beyond HRV measures with both sympathetic and parasympathetic influences (Luque-Casado et al., 2016; Mulder and Mulder, 1981).

Literature is limited and conflicted in characterizing the relationship between vagal withdrawal and SA performance in healthy adults. The majority of work has focused on the autonomic demands of SA (i.e., changes in autonomic functioning during SA) rather than characterizing patterns of autonomic functioning associated with optimal SA (Luque-Casado et al., 2016; Porges, 1992; Porges and Raskin, 1969; Walter and Porges, 1976). Researchers have theorized that minimal vagal withdrawal during assessments of cognitive control may represent a greater ability of the parasympathetic nervous system to respond efficiently to task demands (Laborde et al., 2018). Conserving autonomic resources during SA may also lead to less severe time-on-task performance decrements, improving overall performance. In contrast, other work suggests moderate vagal withdrawal may benefit cognitive control, potentially reflecting essential increases in arousal and mental exertion during cognitive stress optimal for task performance (Chin and Kales, 2019; Marcovitch et al., 2010; Porges et al., 1975). Elucidating the underlying parasympathetic dynamics during optimal SA may be a central pillar in advancing the ability of behavioral techniques, medical devices, and HRV biofeedback (HRVB) to improve sustained attention in clinical and healthy adults.

The gradual-onset continuous performance task (gradCPT) is a validated, computerized measure of sustained attention sensitive to deficits in attentional engagement (Esterman et al., 2013). The gradCPT characterizes individual differences in sustained attention and within-participant fluctuations in attentional states (Esterman et al., 2013). Using the gradCPT to characterize sustained attention quantifies discrimination ability (d'). This measure utilizes signal detection theory to measure a participant's ability to discriminate between targets and distractors (Fortenbaugh et al., 2015). D' is independent of response bias compared to commission errors (CEs) and omission errors (OEs) in isolation, as CEs and OEs can be influenced by both perceptual sensitivity (d') and bias (Fortenbaugh et al., 2017b). The gradCPT also characterizes the coefficient of variation of RT (CV), also known as RT variability, as a measure of attentional stability (Esterman et al., 2013). RTs that deviate significantly from the rate of stimulus presentation represent reduced attention. Extremely fast RTs and commission errors indicate a participant's inability to account for the potential need to inhibit responses, which can be characterized as mindless responding. On the other hand, extremely slow RTs and omission errors demonstrate inefficient processing of visual stimuli in real-time and task disengagement. D' and CV are highly correlated in this task and represent an "ability" factor, as opposed to strategy (Fortenbaugh et al., 2015). This ability factor has demonstrated unique neural correlates during optimal and sub-optimal attentional states (Yamashita et al., 2021), effects of reward (Esterman et al., 2014), and lifespan trajectory (Fortenbaugh et al., 2015). Both primary outcome measures of the gradCPT offer unique insights into SA beyond mean-based estimates of accuracy.

To provide a more holistic characterization of the relationship between vmHRV and sustained attention, it is important to also include dispositional factors related to attention in daily life. While assessments of sustained attention may be sensitive to individual differences in a laboratory setting, it is unclear if performance generalizes to abilities and behaviors reliant on SA in daily life. Assessing the relationship between vmHRV and these dispositional factors may support vmHRV as an ecologically valid physiological measure of dispositional SA, immensely increasing the potential real-world usability of HRV as an autonomic biomarker of SA. Media-multitasking (Madore et al., 2020), mindfulness (Petranker and Eastwood, 2021), attentional errors in daily life (Rosenberg et al., 2013; Smilek et al., 2010), and self-regulation (Wei et al., 2012) have been found to influence or be influenced by sustained attention. Specifically, increased levels of media-multitasking are associated with deficits in sustained attention and memory (Madore et al., 2020). Increased media-multitasking is thought to reflect and promote shallow engagement and impulsivity (Madore et al., 2020). Increased ability to orient and execute behaviors based on goals (self-regulation) and a greater general tendency to be aware and attentive to the present moment in daily life (mindful attention) have been associated with greater attentional control (Gorman and Green, 2016; Liston et al., 2009; Ophir et al., 2009), and higher resting vmHRV (Reynard et al., 2011; Shearer et al., 2016).

Despite the importance of characterizing the role of parasympathetic function to dispositional factors of SA in daily life, no study to date has explored if there is a relationship between resting vmHRV and self-reported media multitasking habits, attentional lapses in daily life, or self-regulation.

1.1. Aims of current study

We aimed to characterize the relationship between parasympathetic functioning and SA using the gradual onset continuous performance task (gradCPT) and self-report dispositional factors related to SA. This is the first study to examine vmHRV and SA using the gradCPT, which allowed us to utilize a decade of research in clinical and healthy samples to contextualize findings in the current study beyond mean-based estimates of reaction time and accuracy. Further, expanding the current understanding between vmHRV, SA, and dispositional factors related to SA may be an important building block for future research in applied human factors and psychophysiology. Specifically, this work aimed to functionally identify individuals at greater risk of attentional lapses based on a brief assessment of autonomic functioning. Further, this work aimed to potentially implicate vmHRV as a measure sensitive to individual differences in SA in the lab and in the real world, substantially increasing the utility of vmHRV in potential applications of non-invasive monitoring and interventions to improve SA. Addressing this knowledge gap may help inform future work that aims to improve safety and ameliorate occupational hazards in fields in which attentional lapses pose a substantial risk, such as military operations, air-traffic control, and driving.

2. Methods

The present manuscript represents a registered report. Hence, study hypotheses and methods were registered prior to collecting, analyzing, or interpreting the data. Raw data for this registered reported are posted on Open Science Framework at https://osf.io/8cqhv/.

2.1. Participants

100 young adults aged 18–28 years old [age (M = 20.6, SD = 3.08), 57 women] from the Tufts residential community were compensated one hour of course credit or $15 for one hour of participation in the experiment. Two participants reported to be between 18 and 28 years old on our prescreen were excluded from all analyses for being older than 28 years old during participation in the study. We subsequently ran two more participants to reach our defined sample of 100 participants aged 18–28 years old. Participants who reported they had been diagnosed with or were taking medication for any cardiopulmonary, psychiatric, or neurological condition were excluded. Participants were also excluded for depression, anxiety, and current nicotine use. We instructed participants to abstain from alcohol consumption and recreational drug use for at least 24 h before the study. Participants were also advised to consume a light meal 2 h before the experiment. We only recruited participants who indicated that they had normal hearing and normal or corrected-to-normal vision. Participants read and signed an informed consent statement before the beginning of the experimental session and were informed about their right to leave the experiment at any time. All data were deidentified before data analysis and reporting. The experimental protocol was approved by the Tufts University Instructional Review Board (IRB; protocol 00001421) with secondary approvals by the U.S. Army DEVCOM Soldier Center Human Research Protection Official (HRPO; protocol 21–004) and complied with the ethical standards laid down in the 1964 Declaration of Helsinki.

2.2. Gradual-onset continuous performance task

The gradCPT is a go/no-go continuous performance task designed to measure sustained attentional control (Esterman et al., 2013). During the 8-minute version of the task, participants viewed a series of grayscale scene images that gradually transition from one to the next approximately every 800 ms using linear pixel-by-pixel interpolation. The gradCPT required participants to respond via button press to frequently occurring city images (90 % of stimuli) and withhold responses to rare mountain images (10 % of stimuli). In addition to the gradual and overlapping nature of the task, the rapid tempo encouraged a consistent reaction time (RT), as RTs that are too fast lead to errors of commission to rare mountain scenes and RTs that are too slow lead to errors of omission to common city scenes, both of which are associated with lower accuracy. Data exclusion criteria followed prior protocols; specifically, data was discarded for any participant who has a prolonged period (30 s or more) without a response, as this indicates noncompliance with task instructions (Fortenbaugh et al., 2015).

The primary measures of sustained attention ability on the gradCPT were discrimination ability (d') and coefficient of variation in reaction time (CV) (Esterman et al., 2013, 2019; Fortenbaugh et al., 2015). Each was calculated using custom R (R Core Team, 2000) and Matlab (Mathworks) scripts. Specifically, d' was calculated with signal detection analyses to quantify the ability to discriminate between targets/nontargets independent of response strategy (Macmillian and Creelman, 1991). Higher d' is indicative of greater accuracy on the gradCPT. CV, a measure of RT variability, was calculated from correct responses to city scenes using the standard deviation of RT divided by the mean RT (Esterman et al., 2013). Higher CV is associated with poorer sustained attention ability (Fortenbaugh et al., 2015).

2.3. Self-reported questionnaires

2.3.1. Attention-related cognitive errors scale (ARCES)

The ARCES (Carriere et al., 2008; Cheyne et al., 2006; Smilek et al., 2010) assesses real-world errors in routine daily activities caused by lapses in sustained attention, drawing significant work from the Cognitive Failures Questionnaire (Reason, 1984). The ARCES questionnaire consists of 12 questions using a Likert scale ranging from (1) never to (5) very often. Scores may range from 12 to 60 and was used as a continuous measure in all analyses. The ARCES has been demonstrated to have excellent psychometric properties and high internal reliability (Carriere et al., 2008; Cheyne et al., 2006; Smilek et al., 2010). Previous work has demonstrated the self-reported score on ARCES is correlated with overall performance on the Sustained Attention to Response Task (Smilek et al., 2010). The ARCES has excellent internal consistency (α = 0.90) (Roll et al., 2019).

2.3.2. Short Form Self-Regulation Questionnaire (SSRQ)

The SSRQ is a 31-item questionnaire sensitive to individual differences in one's capacity to regulate goal-oriented behavior (Neal and Carey, 2005). Using factor analysis, Neal and Carey found two distinct factors, labelled as impulse control and goal setting. Sample items included, "I am able to resist temptation", and "I usually keep track of my progress towards my goals". Participants rate how applicable each statement is based on a 5-point Likert scale ranging from (1) strongly disagree to (5) strongly agree. The SSRQ has high internal reliability (r = 0.87), as well as convergent and discriminant validity (Neal and Carey, 2005).

2.3.3. Media Multitasking Measure – Short (MMM-S)

The MMM-S is a 9-item measure of media multitasking based on the most prevalent media multitasking behaviors in adolescents (Baumgartner et al., 2017). The questions on the MMM-S measure four different media use activities: listening to music, watching TV, sending messages, and using social media sites. For all activities, participants report the frequency in which they engage in these activities simultaneously. The Cronbach's alpha for the MMM-S has been found to range from 0.90 to 0.91, suggesting excellent internal consistency (Baumgartner et al., 2017; Sansevere and Ward, 2021).

2.3.4. Mindful Attention and Awareness Scale (MAAS)

The MAAS consists of 15 self-report questions that assess the general tendency of the participant to be aware and attentive to the present moment in daily life (Brown and Ryan, 2003). The MAAS has been demonstrated to have excellent test-retest reliability and good internal consistency (α = 0.88) (Cheyne et al., 2006). Lower scores on the MAAS have been linked to higher levels of social anxiety, psychological disturbances, and rumination (Carlson and Brown, 2005; Kocovski et al., 2009).

2.4. Heart rate variability assessment and analyses

HRV was calculated from the continuous, non-invasive digital HRV recording using a Zephyr Bioharness chest strap, with a sampling frequency of 250 Hz. HRV was assessed continuously throughout the experiment. Interbeat intervals (IBIs) were processed and analyzed in Kubios Premium HRV (version 3.4) using automatic artifact correction in which artifacts are detected from dRR series, the time series of differences between successive RR intervals (Lipponen and Tarvainen, 2019). The dRR series allowed robust separation between ectopic and misplaced beats from the normal sinus rhythm. Identified artifacts were corrected using a cubic spline interpolation.

The continuous IBIs were subjected to fast Fourier transformation for frequency domain measures of LF power (0.04–0.15 Hz) and HF power (0.15–0.40 Hz) (Task Force of the European Society, 1996). The 10-minute baseline was manually inspected for artifacts. To minimize the potential influence of acclimation to the study (Laborde et al., 2017), we extracted a 5-minute segment during baseline that was closest to the cognitive testing period (end of resting baseline) that met the proposed artifact threshold of lower than 5 % of the sample (Tarvainen et al., 2014). Time points used to extract baseline measurements for each participant and the percentage of beats corrected were reported for both the resting baseline and task-based measurements in data files located in our open science foundation data repository (https://osf.io/8cqhv/).

Our primary measure of vmHRV was the time domain metric RMSSD (root mean square of the successive differences between normal heartbeats; ms^2). RMSSD violated the Shapiro-Wilks test of normality ($p <$ .001) and thus was log transformed (log-RMSSD) in order to reduce positive skew and meet assumptions of normality for statistical tests (Royston, 1992). Log-RMSSD is considered a marker of vmHRV, largely independent of the potential effects of respiration rate. Resting vmHRV has been previously demonstrated to be a predictor of individual differences in attentional maintenance and performance variability (Laborde et al., 2017; Shaffer and Ginsberg, 2017; Siennicka et al., 2019; Spangler et al., 2018; Williams et al., 2016). To adhere to standards for reporting HRV, we report resting and task-based HRV measures of SDNN, LF absolute power (0.04–0.15 Hz), HF absolute power (0.15–0.40 Hz), and P50NN (Laborde et al., 2017; Quintana et al., 2016) in Table 1. HF/LF is not reported in the current study, considering its questionable theoretical understanding and common misinterpretation in literature (Goldstein et al., 2011).

Table 1
Resting and task-based measures of heart rate variability.

	RMSSD	SDNN	LF	HF	PNN50
Resting baseline HRV measures					
N	84	84	84	84	84
Mean	36.72	41.25	1043.47	748.97	16.80
Median	35.27	39.39	868.37	463.03	13.10
Standard deviation	19.27	15.79	762.70	950.72	15.92
Minimum	7.81	13.37	93.29	28.22	0.00
Maximum	93.27	89.23	4519.31	5656.14	62.45
Task-based HRV measures					
N	84	84	84	84	84
Mean	42.82	42.83	986.63	876.71	21.64
Median	39.07	40.56	698.86	486.11	17.41
Standard deviation	23.36	17.35	814.38	1315.76	18.18
Minimum	11.86	15.05	123.70	53.68	0.00
Maximum	137.62	110.49	5021.94	9128.01	75.65

Note. HF = high frequency power, HRV = heart rate variability, LF = low frequency power, PNN50 = The proportion of NN50 divided by the total number of NN (R-R) intervals, RMSSD = root mean square of the successive differences between normal heartbeats, SDNN = standard deviation of interbeat interval after artifact removal.

2.5. Sample size calculations

This is the first study to examine resting vmHRV and sustained attention with the gradCPT in healthy younger adults. To conduct our power analysis, we relied on effect sizes obtained in adjacent literature, as well as conventional statistical literature on effect sizes for hierarchical linear regression in behavioral sciences (Cohen, 1988). A power analysis was conducted using G*Power software (Cohen, 1988; Faul et al., 2007) using the following parameters: Linear multiple regression: Fixed model R^2 increase, tail(s) = two, effect size $f^2 = 0.15$, alpha = 0.05; power = 0.90, number of tested predictors = 1 [log-RMSSD], Total number of predictors = 5 [log-RMSSD, age, gender, BMI, time of day], design = linear multiple regression, fixed model, R^2 increase, and it indicated that 73 participants [noncentrality parameter $\delta = 10.95$, Critical $t = 3.98$, $Df = 67$, Total sample size = 73, actual power = 0.90] were required to detect a medium effect size after accounting for four covariates (age, gender, body mass index, time of day). This sample size was comparable to three studies relevant to the current work ($n = 74$, Siennicka et al., 2019), ($n = 83$, Spangler et al., 2018), and ($n = 104$, Williams et al., 2016). To account for potential data-loss due to task noncompliance and/or signal artifact, we ran 100 participants through the protocol.

2.6. Procedure

Participant recruitment was conducted through SONA and community-based outreach techniques (posters & word of mouth). Twenty-four hours before the experiment, participants were reminded of the upcoming study. Participants arrived between the hours of 9:00 and 17:00 to the experiment. Upon arrival, participants again verified they qualified for the study based on the screening criteria and read through the informed consent document. If participants did not sign the informed consent document, they were released without compensation. If participants gave informed consent, we then measured weight and height to calculate body mass index and asked participants to complete a brief demographics questionnaire of age and gender. After these measurements, we fitted participants with the Zephyr Bioharness, and we asked if they needed to use the bathroom (Laborde et al., 2017). We then instructed participants to sit in a chair in an upright position, with their arms on the keyboard to maximize similarity to the position participants were in during subsequent task conditions. We then asked participants to quietly sit in this position and fixate on a central cross in the center of the screen. After 10 min, we asked participants to take part in the cognitive assessment, then subsequently complete questionnaires. The order of questionnaires (ARCES, MAAS, SSRQ, MMM-S) was randomized to minimize the potential for order and fatigue effects. Participants then took off the heart rate monitor, received a study debriefing form and compensation for their time and participation in the study (Fig. 1).

2.7. Registered confirmatory analysis plan

All data, scripts, and materials are stored on a repository hosted by the Center for Open Science at https://osf.io/8cqhv/ to encourage transparency and replicability. This includes both the estimated raw interbeat interval files for resting and task-based HRV recordings, gradCPT processing scripts and data files, survey processing scripts and data files, and statistical analysis scripts.

Details on registered hypotheses, analyses, and interpretations are reported in Tables 2–5. Sample-based measures of internal consistency [Cronbach's coefficient α (Cronbach, 1951)] were obtained for gradCPT (reaction time) and self-reported questionnaires (ARCES, SSRQ, MAAS, and MMM-S).

2.7.1. Outcome neutral criteria analysis plan (registered)

We conducted three outcome neutral tests (Table 2) to validate whether participants exhibit time-on-task performance decrements on

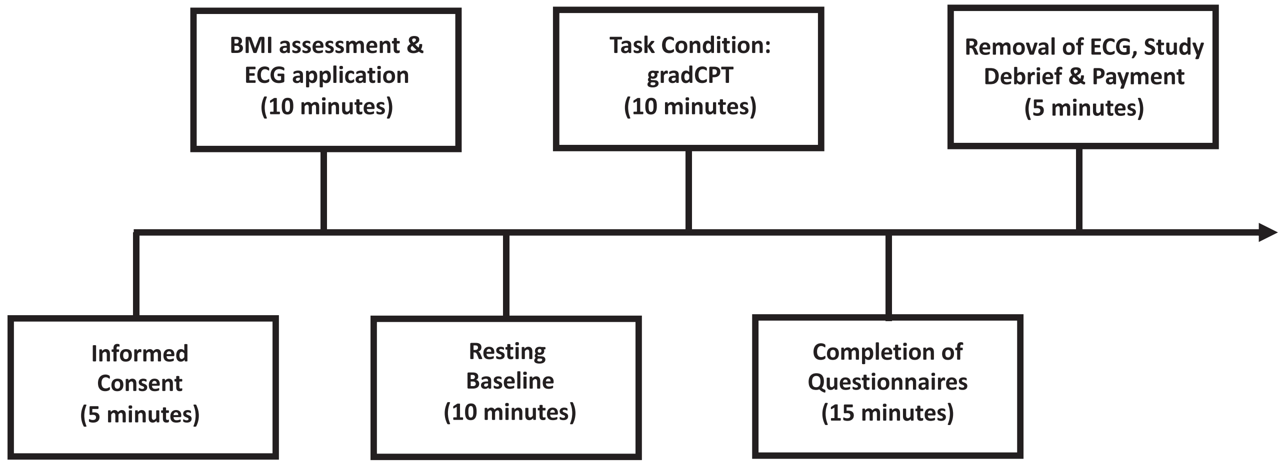

Fig. 1. Proposed study protocol across a 60-minute experimental assessment.

Table 2
Registered hypotheses.

Hypothesis	Evaluation methods
Outcome neutral criteria (resting RMSSD and RMSSD reactivity)	
H_1: d' would be lower on the second half of the gradCPT compared to the first	• *t*-test • Bayes factors *t*-test
H_2: CV would be higher on the second half of the gradCPT compared to the first	
Outcome neutral criteria (RMSSD reactivity only)	
H_3: Log-RMSSD would be lower during cognitive testing compared to the resting baseline	
Confirmatory analyses	
H_4: Resting log-RMSSD would be positively associated with d'	• Sequential linear regression • Bayesian linear regression • Structural regression
H_5: Resting log-RMSSD would be negatively associated with CV	
H_6: Resting log-RMSSD would be negatively associated with ARCES total score	
H_7: Resting log-RMSSD would be positively associated with MAAS total score	
H_8: Resting log-RMSSD would be positively associated with SSRQ total score	
H_9: Resting log-RMSSD would be negatively associated with MMM-S total score	

Note. ARCES = attention-related cognitive errors survey; CV = coefficient in variation of reaction timed$'$ = discrimination ability; gradCPT = gradual-onset continuous performance task; MAAS = mindful attention awareness scale; MMM-S = short media-multitasking measure RMSSD = root mean square of the successive differences between normal heartbeats; SSRQ = short self-regulation questionnaire.

the gradCPT (i.e., lower d$'$ and higher CV during second half of cognitive testing compared to first half), and if they exhibit a decrease in log-RMSSD during cognitive testing relative to baseline (vagal withdrawal). Conditional on establishing effects for H_1 and H_2, we proceeded with confirmatory analyses of resting log-RMSSD and measures of SA (H_4–H_9). Conditional on establishing effects for H_1, H_2, and H_3, we would have proceeded with regression analyses involving log-RMSSD

Table 4
Proposed guidelines for interpretation of linear regression findings.

Independent predictors	Support for hypothesis
	p-value interpretation
$p > .05$[a]	Failure to reject the null hypothesis
$p < .05$[a]	Rejection of the null hypothesis

[a] Before FDR correction for multiple comparisons.

Table 5
Proposed guidelines for interpretation of Bayes factors findings (Jeffreys, 1961).

BF_{10}	Interpretation of findings
<0.01	Decisive evidence for null hypothesis
0.01–0.03	Very strong evidence for null hypothesis
0.03–0.10	Strong evidence for null hypothesis
0.10–0.33	Substantial evidence for null hypothesis
0.33–1	Anecdotal evidence for null hypothesis
1	No evidence
1–3	Anecdotal evidence for alternative hypothesis
3–10	Substantial evidence for alternative hypothesis
10–30	Strong evidence for alternative hypothesis
30–100	Very strong evidence for alternative hypothesis
>100	Decisive evidence for alternative hypothesis

Note. BF_{10} represents evidence in favor of the alternative hypothesis.

Table 3
Registered regression analyses.

Purpose	Approach	Independent measures	Dependent measures	Number of tests	Covariates
Registered: Association between resting vmHRV and dependent measures	Sequential linear regression and Bayes factors regressions with and without covariates	Resting log-RMSSD	GradCPT Performance (*d*$'$, *CV*) Dispositional Surveys (*ARCES*, *SSRQ*, *MMM-S*, *MAAS*)	6 (1 per dependent measure) with FDR correction for multiple comparisons	*Age*, *Gender*, *BMI*, *Time of day*

Note. ARCES = attention-related cognitive errors survey; BMI = body mass index. CV = coefficient in variation of reaction time; d$'$ = discrimination ability; GradCPT = gradual-onset continuous performance task; MAAS = mindful attention awareness scale; MMM-S = short media-multitasking measure; log-RMSSD = log-transformed root mean square of the successive differences between normal heartbeats; SSRQ = short self-regulation questionnaire; vmHRV = vagally-mediated heart rate variability.

reactivity. Based on our findings, H_1 and H_2 were supported, but not H_3. Thus, we only performed confirmatory analyses of resting log-RMSSD and measures of SA (H_4–H_9) and further excluded log-RMSSD reactivity from the planned structural regression.

2.7.2. Regression analysis plan (registered)

To assess the relationship between resting vmHRV and sustained attention, we conducted sequential linear regressions and Bayesian linear regressions (Tables 2–4) predicting d' (discrimination ability), CV (reaction time variability); as well as the total scores from the ARCES, SSRQ, MAAS and average score from MMM-S.

The first step in the models included log-RMSSD of the 5-minute baseline period. The second step included important characteristics known to impact vmHRV; age (continuous, in years), gender (factorial, entered as 0 = male, 1 = female), body mass index (BMI; continuous, kg/m^2) (Koenig et al., 2014; Koenig and Thayer, 2016; Thayer et al., 2012), and time of day of assessment (continuous, coded as 0 = 9 AM–12 PM, 1 = 12:01 PM–3 PM, 2 = 3:01 PM–5:00 PM). The Benjamini and Hochberg (1995) method of false discover rate (FDR) correction was used for analyses of resting vmHRV to correct for multiple comparisons. FDR correction attempts to account for the expected proportion of false discoveries among the rejected hypotheses (Benjamini and Hochberg, 1995). Analyses of vagal reactivity (Δ RMSSD from baseline to task) were excluded to due to an increase in log-RMSSD from rest to task (H_3). We used Bayes factors to complement the traditional null hypothesis testing approach in the current study. Which allowed us to evaluate evidence for an alternative hypothesis, relative to a null hypothesis (Table 5). Analyses of Bayes factors were conducted in JASP (JASP Team, 2022). The prior for Bayesian *t*-tests was based on the default JASP Cauchy distribution of 0.707. Bayes factor robustness checks for Bayesian t-tests were used to calculate Bayes factors for a range of priors and are reported in Supplemental Tables S1–S3. The fit of the data under the null distribution was compared to the fit under the alternative hypothesis. Tables 7–8 report the regression coefficients, the standard error of the unstandardized regression coefficients, standardized regression coefficients and *p*-values for all variables (age, gender, BMI, time of day and log-RMSSD) across all linear regression models. For Bayesian linear regression models (Supplemental Tables S3–S8), we reported the *posterior probability* of each model (P(M|data)), relative predictive adequacy of the given model compared to the best fitting model (BF_{10}), variance accounted for in the outcome variable by the predictor (R^2), and the inclusion Bayes factor (posterior inclusion odds / the prior inclusion odds; $BF_{inclusion}$). Bayesian linear regressions used the default JZS prior of $r = 0.354$ for hypothesis testing.

2.7.3. Structural equation modeling analysis plan (registered)

We conducted structural regressions in Mplus version 8.10 (Muthén and Muthén, 2017) in which we assessed to what extent resting log-RMSSD predicted individual differences in lab-based and dispositional measures of SA. Specifically, we assessed two competing models that assumed different latent variable structures and factor loadings for dependent measures. Both models 1 and 2 account for age, sex, BMI, and time of day as covariates. Model 1 included log-RMSSD predicting two distinct latent variables reflecting laboratory-based SA (d' and CV) and dispositional SA (ARCES, SSRQ, MMM-S, and MAAS). Model 2 included log-RMSSD predicting one latent variable of SA (d′, CV, ARCES, SSRQ, MMM-S, and MAAS). Testing these models offered several complements to the sequential linear regression and Bayes factors approaches listed above. First, the models allowed us to include multiple dependent variables in the same model, reducing the risk of false positives from multiple comparisons and the risk of false negatives when using multiple-comparison correction. Second, models 1 and 2 allowed us to understand the latent variable structures that represented SA in the current experiment. Based on current literature, it is unclear if assessments in the lab would be related to behaviors in daily life. Testing which model is most appropriate for the data informed us to whether a unifying framework of SA (i.e., lab-based and dispositional measures represent overall SA), or a two distinct factor framework (i.e., laboratory measures of SA are distinctly different than dispositional measures of SA) was more appropriate. We report global measures of model fit across multiple indices (Chi-square Goodness of Fit, root mean square error of approximation (RMSEA), standardized root means square residual (SRMR), comparative fit index (CFI), and local model fit (standardized residuals for covariances)). Interpretations for model performance can be found in Table 6. Standardized and unstandardized Beta values were reported for all paths indicated in models 1 and 2. Standardized and unstandardized latent factor loadings (factor loadings, intercepts, and residual variances) were reported for models 1 and 2 as well. We also reported the distribution and scedasticity of residuals of the model prediction to ensure assumptions were met.

2.8. Data cleaning

Participants who failed to respond for 30 s or longer during cognitive testing were excluded from analysis for task non-compliance. Participants who perform two standard deviations below the mean for d` and CV were excluded from analysis for poor task-adherence. These criteria led to no participants being excluded from the study. Dependent measures of d', CV, attentional errors in daily life, mindfulness, media multitasking and self-regulation were assessed for normality using the Shapiro-Wilks test of normality ($p < .05$) (Royston, 1992). Based on a violation of normality, the dependent variable for attentional errors in daily life was log-transformed in order to reduce positive skew and meet assumptions of normality for statistical tests.

2.9. Deviations from registration

Although we did our best to ensure that we followed our registered plan, there were several minor deviations from the Stage 1 manuscript. First, we utilized the Zephyr Bioharness 3 chest belt instead of the Polar H10 heart rate sensor due to difficulties pairing the Polar H10 heart rate sensor with our Bluetooth precision timing system. We contacted the manufacturer (Polar Electro Oy, Kempele, Finland) but were not provided a solution for the issue. Second, we omitted participant instructions regarding excessive exercise, regular sleep-wake cycle, and caffeine consumption due to an oversight error in the participant recruitment system. This has been listed as a limitation for the current study. We also attempted to address caffeine consumption in post-hoc exploratory analyses assessing the relationship between resting log-RMSSD and measures of SA within a sub-sample of participants who report to not consume caffeine habitually. Third, gender was included in

Table 6
Proposed guidelines for interpretation of structural regression findings.

Model-fit criteria	Acceptable level	Interpretation
Global model-fit criteria		
Chi-square	Tabled x^2 value	Compares obtained x^2 value with tabled value for given *df* ($p > .05$) indicates good model fit
Standardized root-mean square residual (SRMR)	<0.08	Value <0.05 indicates a good model fit while values of 0.05 to 0.08 are considered an adequate fit
Root-mean-square of approximation (RMSEA)	0.05 to 0.08	Value of 0.05 to 0.08 indicate close fit
Comparative fit index (CFI)	>0.95	Values above 0.95 are considered a good fit, with values closer to 1 better model fit
Local model-fit criteria		
Standardized residuals for covariances (individual variables)	<|2|	Values less than |2| suggest good local fit for individual variables

analyses as a covariate instead of sex. Gender was the intended covariate of interest during registration to account for HRV differences across gender (Voss et al., 2015), but was erroneously written as sex in the original stage 1 submission.

3. Results

3.1. Measures of reliability and internal consistency (registered)

Measures of Cronbach's alpha (internal consistency) were the following for survey-based measures: Attention-related cognitive errors scale (ARCES, $\alpha = 0.84$), Mindful Attention and Awareness Scale (MAAS, $\alpha = 0.86$), Media Multitasking Measure – Short (MMM-S, $\alpha = 0.85$), and Short Form Self-Regulation Questionnaire (SSRQ, $\alpha = 0.89$). Mean reaction time across quartiles of gradCPT performance exhibited an internal consistency of $\alpha = 0.93$.

3.2. Outcome neutral criteria (registered)

Based on H_1 and H_2, we hypothesized participants would exhibit time-on-task performance decrements on the gradCPT (i.e., lower d' and higher CV during second half of cognitive testing compared to first half) (Table 2). In line with our prediction, paired frequentist and Bayesian *t*-tests revealed participants exhibited significantly lower d' ($t(99) = 5.30$, $p < .001$, $BF_{10} = 19{,}051$), and higher CV ($t(99) = -5.17$, $p < .001$, $BF_{10} = 11{,}243$) during the second half of cognitive testing compared to the first half. Based on H_3, we hypothesized participants would exhibit a decline in log-RMSSD from resting baseline to task (vagal withdrawal). Contrary to our prediction, paired frequentist and Bayesian t-tests revealed participants' log-RMSSD increased from rest to task ($t(77) = -5.10$, $p < .001$, $BF_{10} = 6660$). We then performed confirmatory analyses of resting log-RMSSD and measures of SA (H_4–H_9) but further excluded exploratory vagal withdrawal from the registered frequentist, Bayesian, and structural regressions as outcome neutral hypothesis H_3 was not supported.

3.3. Frequentist and Bayesian linear regression analyses (registered)

3.3.1. Task-based regression analyses

For the regression model predicting discrimination ability (d'), we entered resting log-RMSSD into model one. Resting log-RMSSD ($\beta = -0.08$, $p = .45$) did not account for a statistically significant amount of variance in d' ($R^2 = 0.01$, $F(1, 82) = 0.58$, $p = .45$). Age, gender, BMI, and time of day were entered in model two. After accounting for covariates, resting log-RMSSD ($\beta = -0.09$, $p = .41$) was still not significantly associated with d' (Table 7). Similarly, resting log-RMSSD was not associated with d' in any of the Bayesian regression models (P(M|data) $= 0.04$, $BF_{10} = 0.29$, $R^2 = 0.01$, $BF_{inclusion} = 0.16$; Supplemental Table S4).

Table 7
Regression summary table testing the potential association of baseline log-transformed RMSSD and task-based sustained attention.

Variable	D′			CV		
	B	*SE(B)*	β	*B*	*SE(B)*	β
Log-RMSSD	−0.13	0.16	−0.09	−0.01	0.01	−0.06
Age	0.04	0.03	0.16	−0.00	0.00	−0.23
Gender	−0.07	0.17	−0.09	0.03	0.01	0.58*
BMI	−0.02	0.02	−0.19	0.00	0.00	0.21
Time of Day	−0.03	0.12	−0.03	0.00	0.01	0.03
Model 1 fit	$R^2 = 0.01$, $F(1, 82) = 0.58$, $p = .45$			$R^2 = 0.00$, $F(1, 82) = 0.09$, $p = .77$		
Model 2 fit	$R^2 = 0.05$, $F(5, 78) = 0.81$, $p = .55$			$R^2 = 0.15$, $F(5, 78) = 2.76$, $p = .02$		

Note. $p_{FDR} < .05$* indicates significance after false discovery rate correction (FDR). B = effect size, β = standardized effect size, BMI = body mass index, CV = reaction time variability, D′ = discrimination ability, log-RMSSD = log-transformed root mean square of the successive differences between normal heartbeats, SE(B) = standard deviation for effect size, time of day = time of day of cognitive assessment.

For the regression model predicting reaction time variability (CV), we entered resting log-RMSSD into model one. Resting log-RMSSD ($\beta = -0.03$, $p = .77$) did not account for a statistically significant amount of variance in CV ($R^2 = 0.00$, $F(1, 82) = 0.09$, $p = .77$). Age, gender, BMI, and time of day were entered into model two. After accounting for covariates, resting log-RMSSD ($\beta = -0.06$, $p = .58$) was still not associated with CV (Table 7). Similarly, resting log-RMSSD was not significantly associated with CV in any of the Bayesian regression models (P(M|data) $= 0.01$, $BF_{10} = 0.23$, $R^2 = 0.00$, $BF_{inclusion} = 0.55$, Supplemental Table S5). We did find significant gender differences in CV after FDR correction, in which women exhibited greater reaction time variability compared to men ($\beta = 0.59$, $p < .01$, $p_{FDR} = .04$; P(M|data) $= 0.14$, $BF_{10} = 4.53$, $R^2 = 0.08$, $BF_{inclusion} = 3.46$).

3.3.2. Dispositional survey-based regression analyses

For the regression model predicting attentional errors in daily life (ARCES), we entered resting log-RMSSD into model one. Resting log-RMSSD ($\beta = 0.08$, $p = .50$) did not account for a statistically significant amount of variance in ARCES ($R^2 = 0.01$, $F(1, 82) = 0.47$, $p = .50$). Age, gender, BMI, and time of day were entered into model two. After accounting for covariates, resting log-RMSSD ($\beta = 0.04$, $p = .71$) was still not associated with ARCES (Table 8). Similarly, log-RMSSD was not significantly associated with ARCES in any Bayesian regression models (P(M|data) $= 0.01$, $BF_{10} = 0.28$, $R^2 = 0.01$, $BF_{inclusion} = 0.37$, Supplemental Table S6). We did find significant gender differences in ARCES after FDR correction, in which women reported greater attentional errors in daily life compared to men ($\beta = 0.53$, $p = .02$, $p_{FDR} < .05$; P(M|data) $= 0.12$, $BF_{10} = 2.55$, $R^2 = 0.06$, $BF_{inclusion} = 1.75$).

For the regression model predicting self-regulation (SSRQ), we entered resting log-RMSSD into model one. Resting log-RMSSD ($\beta = -0.00$, $p = .97$) did not account for a statistically significant amount of variance in SSRQ ($R^2 = 0.00$, $F(1, 82) = 0.00$, $p = .97$). Age, gender, BMI, and time of day were entered into model two. After accounting for covariates, resting log-RMSSD ($\beta = -0.01$, $p = .94$) was not associated with SSRQ (Table 8). Similarly, resting log-RMSSD was not significantly associated with SSRQ in any Bayesian regression models (P(M|data) $= 0.01$, $BF_{10} = 0.04$, $R^2 = 0.00$, $BF_{inclusion} = 0.26$, Supplemental Table S7).

For the regression model predicting media multitasking (MMM-S), we entered resting log-RMSSD into model one. Resting log-RMSSD ($\beta = 0.06$, $p = .61$) did not account for a statistically significant amount of variance in MMM-S ($R^2 = 0.00$, $F(1, 82) = 0.26$, $p = .61$). Age, gender, BMI, and time of day were entered into model two. After accounting for covariates, resting log-RMSSD ($\beta = 0.02$, $p = .83$) was still not associated with MMM-S (Table 8). Similarly, resting log-RMSSD was not significantly associated with MMM-S in any Bayesian regression models (P(M|data) $= 0.03$, $BF_{10} = 0.26$, $R^2 = 0.00$, $BF_{inclusion} = 0.18$, Supplemental Table S8).

Finally, we entered resting log-RMSSD into model one of the regression predicting mindfulness (MAAS). Resting log-RMSSD ($\beta = 0.04$, $p = .70$) did not account for a statistically significant amount of variance in MAAS ($R^2 = 0.00$, $F(1, 81) = 0.15$, $p = .70$). Age, gender, BMI, and time of day were entered into model two. After accounting for covariates, resting log-RMSSD ($\beta = 0.07$, $p = .56$) was still not associated with MAAS (Table 8). Similarly, resting log-RMSSD was not significantly associated with MAAS in any Bayesian regression models (P(M|data) $= 0.03$, $BF_{10} = 0.24$, $R^2 = 0.00$, $BF_{inclusion} = 0.13$, Supplemental Table S9).

3.4. Structural regression analyses (registered)

3.4.1. Model 1

Visual inspection of residuals of the model prediction suggested assumptions of normality and scedasticity were met. The global model fit

Table 8
Regression summary table testing the potential association of baseline log-transformed RMSSD and self-reported measures of dispositional sustain attention.

Variable	ARCES			SSRQ			MMM-S			MAAS		
	B	*SE(B)*	β	*B*	*SE(B)*	β	*B*	*SE(B)*	β	*B*	*SE(B)*	β
Log-RMSSD	0.01	0.04	0.04	−0.24	2.98	−0.01	0.03	0.13	0.02	1.43	2.42	0.07
Age	−0.01	0.01	−0.19	1.43	0.55	0.32+	0.00	0.02	0.01	0.23	0.45	0.07
Gender	0.10	0.04	0.53*	−3.40	3.20	−0.23	0.26	0.14	0.42	−4.21	2.62	−0.37
BMI	−0.00	0.00	−0.10	−0.07	0.28	−0.03	0.01	0.01	0.10	0.01	0.23	0.01
Time of day	−0.01	0.03	−0.05	0.33	2.23	0.02	0.00	0.10	0.00	0.73	1.82	0.05
Model 1 fit	$R^2 = 0.01$, F(1, 82) = 0.47, $p = .50$			$R^2 = 0.00$, F(1, 82) = 0.00, $p = .97$			$R^2 = 0.00$, F(1, 82) = 0.26, $p = .61$			$R^2 = 0.00$, F(1, 81) = 0.15, $p = .70$		
Model 2 fit	$R^2 = 0.12$, *F*(5, 78) = 2.13 $p = .07$			$R^2 = 0.10$, *F*(5, 78) = 1.75, $p = .13$			$R^2 = 0.06$, *F*(5, 78) = 1.01, $p = .42$			$R^2 = 0.04$, F(5, 77) = 0.60, $p = .70$		

Note. $p_{FDR} < .05$* indicates significance after false discovery rate correction (FDR), $p < .05^+$ indicates significance before false discovery rate correction (FDR). ARCES = log-transformed attention related cognitive errors scale, B = effect size, β = standardized effect size, BMI = body mass index, log-RMSSD = log-transformed root mean square of the successive differences between normal heartbeats, MAAS = Mindful Attention Awareness Scale, MMM-S = media multitasking- short form, SE(B) = standard deviation for effect size, SSRQ = short self-regulation questionnaire, time of day = time of day of cognitive assessment.

indices suggested adequate to good model fit [CFI = 0.93; SRMR = 0.07; RMSEA = 0.07 (0.00, 0.12); $x^2(28) = 38.35$, $p = .09$]. For local model fit, all standardized residuals for covariances were < |2|, suggesting good local model fit for variables with the exceptions of SSRQ by MMM-S (2.72) and SSRQ by age (2.54). Similar to our initial regression analyses, resting log-RMSSD was not associated with task-based (B = 0.06, SE(B) = 0.06, β = 0.09, $p = .31$) or dispositional (B = −0.00, SE(B) = 0.03, β = −0.01, $p = .95$) latent factors of sustained attention (SA). Age was also not associated with task-based (B = 0.02, SE(B) = 0.02, β = 0.13, $p = .40$) or dispositional SA (B = −0.01, SE(B) = 0.01, β = −0.20, $p = .17$). Gender was not associated with task-based (B = −0.17, SE(B) = 0.15. β = −0.22, $p = .28$), but was associated with dispositional SA (B = 0.08, SE(B) = 0.04, β = 0.29, $p = .03$) in which men exhibited a higher factor score representing better self-reported sustained attention compared to women. BMI was not associated with task-based (B = −0.01, SE(B) = 0.01, β = −0.10, $p = .45$) or dispositional SA (B = −0.00, SE(B) = 0.00, β = −0.03, $p = .84$). Finally, time of day of assessment given was not associated with task-based (B = −0.00, SE(B) = 0.03, β = −0.00, $p = .95$) or dispositional SA (B = −0.01, SE(B) = 0.02, β = −0.05, $p = .70$).

Standardized latent factor loadings are presented in Fig. 2. Considering factor loadings and residual variances, d' and CV exhibited a weak loading to the latent task-based SA variable, while ARCES, MAAS, SSRQ, and MMMS all exhibited excellent loading to the dispositional SA latent factor (Table 9).

3.4.2. Model 2

Visual inspection of residuals of the model prediction suggested assumptions of normality and scedasticity were met. The global model fit indices all suggest poor model fit [CFI = 0.41; SRMR = 0.17; RMSEA = 0.18 (0.15, 0.22); $x^2(34) = 125.98$, $p < .001$]. For local model fit, several standardized residuals for covariances were > |2|, suggesting poor local model fit for several variables. Specifically, standardized residuals for covariances for gender by ARCES, ARCES by MMM-S, age by SSRQ, and CV by SSRQ were between |2| and |3|. Standardized residuals for covariances for SSRQ by MAAS were between |3| and |4|, whereas ARCES

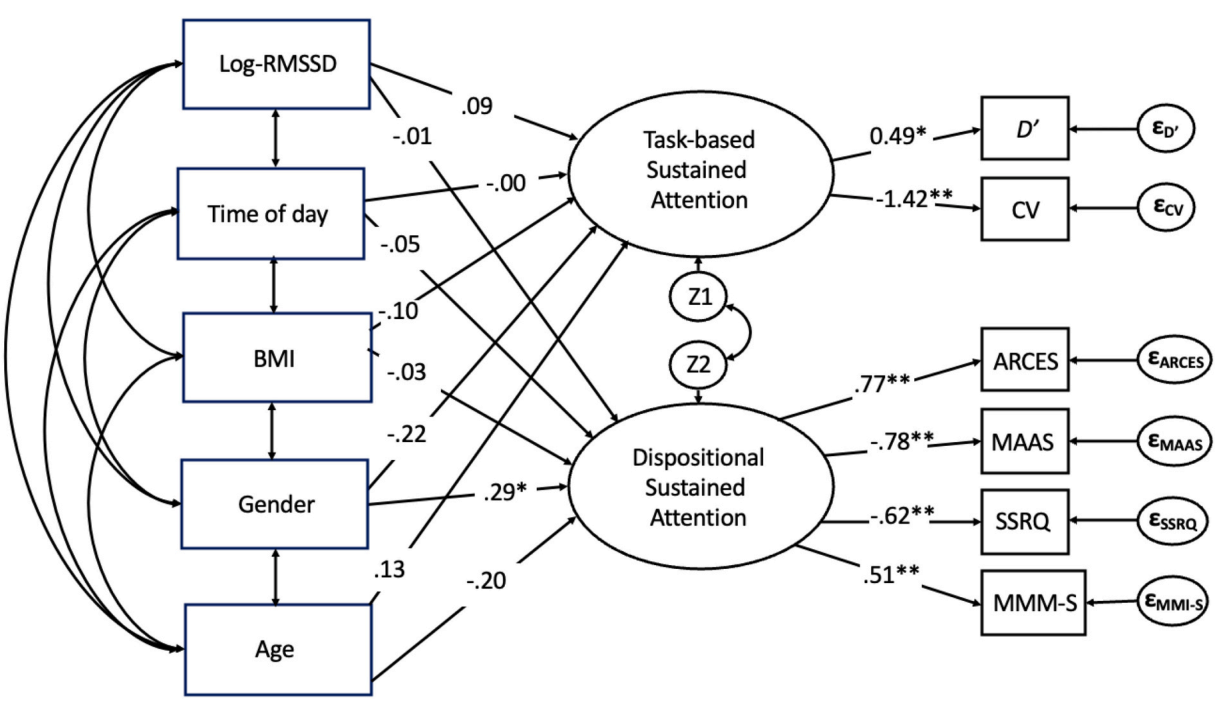

Fig. 2. Dual factor sustained attention structural regression.
Note: $p < .05$*, $p < .01$** denote significant standardized betas and standardized factor loadings. ARCES = log-transformed attention related cognitive errors scale, BMI = body mass index, CV = reaction time variability, d' = discrimination ability, log-RMSSD = log-transformed resting root mean square of the successive differences between normal heartbeats, MAAS = Mindful Attention Awareness Scale, MMM-S = media multitasking- short form, SA = sustained attention latent factor, SSRQ = short self-regulation questionnaire.

Table 9
Unstandardized and standardized model results for the latent variables in structural regression (dual factor).

Item	Unstandardized model			Standardized model		
	Factor loadings	Intercepts	Residual variances	Factor loadings	Intercepts	Residual variances
ARCES	1.00	3.62	0.01	0.77**	19.38	0.41
SSRQ	−62.88**	101.77	133.76	−0.62**	6.93	0.62
MMM-S	2.23**	2.75	0.29	0.51**	4.40	0.74
MAAS	−62.09**	44.05	51.50	−0.78**	3.85	0.39
Variance (SA trait)	0.02			0.89		
D′	1.00	2.76	0.44	0.49*	3.63	0.76
CV	−0.18	0.25	−0.00	−1.42**	5.27	−1.02
Variance (SA task)	0.13			0.93		

Note: $p < .05$*, $p < .01$** denote significant factor loading, ARCES = log-transformed attention related cognitive errors scale, CV = reaction time variability, D′ = discrimination ability, MAAS = Mindful Attention Awareness Scale, MMM-S = media multitasking- short form, SA = sustained attention, SSRQ = short self-regulation questionnaire.

by SSRQ, ARCES by MAAS, and MAAS by MMM-S were between |4| and |5|. Similar to our initial regression analyses, resting log-RMSSD was not associated with SA (B = 0.04, SE(B) = 0.06, β = 0.07, p = .50). Age was not associated with SA (B = 0.01, SE(B) = 0.02, β = 0.12, p = .51). Gender was not associated with SA (B = −0.11, SE(B) = 0.16, β = −0.18, p = .49). BMI was not associated with SA (B = −0.00, SE(B) = 0.01, β = −0.08, p = .57). Finally, time of day of assessment was not associated with SA (B = −0.00, SE(B) = 0.02, β = −0.00, p = .96).

Standardized latent factor loadings are presented in Fig. 3. D', CV, ARCES, MAAS, SSRQ, and MMMS (Table 10) exhibited weak factor loadings to the latent unitary SA variable.

3.5. Exploratory analyses (non-registered)

In addition to our registered analyses, we conducted exploratory analyses to better characterize our findings. Specifically, we assessed vagal withdrawal during cognitive testing (log-RMSSD during the first half of cognitive testing – log-RMSSD during the second half of cognitive testing) in response to the unexpected finding of increased vmHRV from rest to task. Vagal withdrawal during cognitive testing would indicate autonomic demands in response to sustaining attention throughout the task (Luque-Casado et al., 2016), despite not finding vagal withdrawal during cognitive testing relative to rest. Second, we attempted to assess the potential relationship between resting log-RMSSD and measures of sustained attention in participants who reported to not habitually consume caffeine. This analysis aimed to account for the lack of instructions given to participants to abstain from consuming stimulating beverages on the day of cognitive testing by restricting regression analyses to participants that were least likely to have consumed caffeine before study participation (n = 47).

3.5.1. Investigating vagal withdrawal experienced during cognitive task performance

We conducted paired frequentist and Bayesian t-tests to examine the effect of time on task (first 4 min compared to last 4 min of cognitive testing) on vmHRV. The results showed a significant main effect of time ($t(82) = 3.04$, $p = .003$, $BF_{10} = 8.45$) in which participants exhibited greater log-RMSSD during the first half of the task compared to the second half.

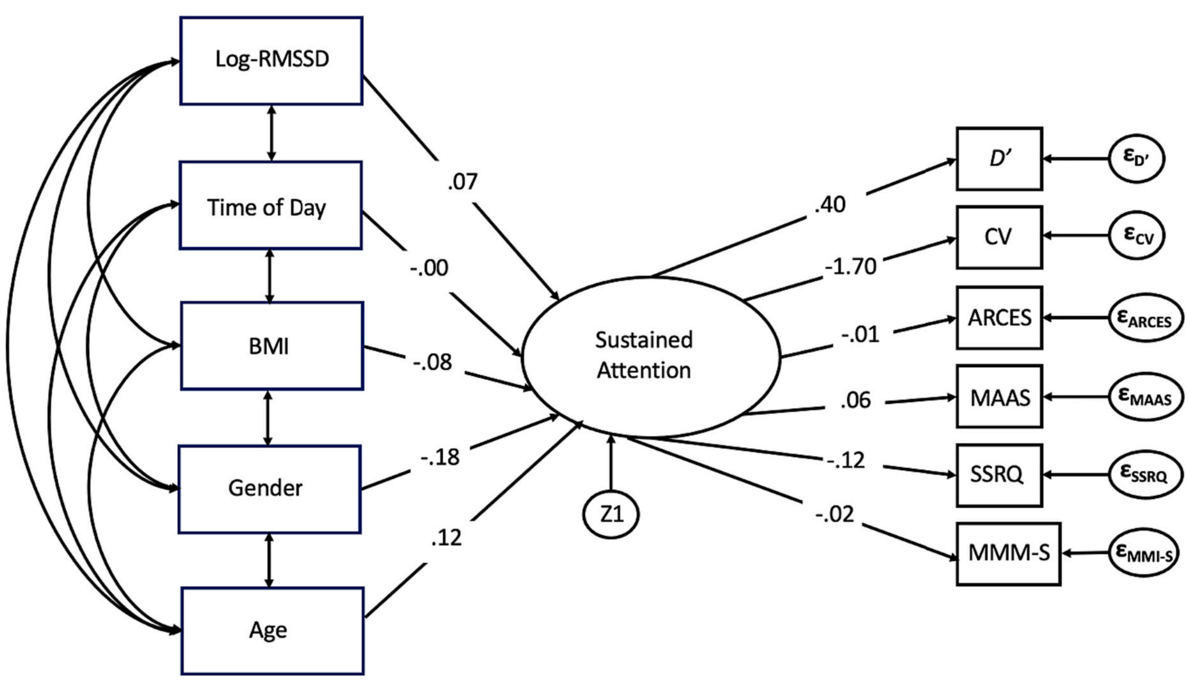

Fig. 3. Single factor sustained attention structural regression.
Note: ARCES = Log-transformed attention related cognitive errors scale, CV = reaction time variability, D′ = discrimination ability, Log-RMSSD = Log-transformed resting root mean square of the successive differences between normal heartbeats, MAAS = Mindful Attention Awareness Scale (MAAS), MMM-S = media multitasking- short form, SA = sustained attention latent factor, SSRQ = short self-regulation questionnaire.

Table 10
Unstandardized and standardized model results for the latent variables in structural regression (single factor).

Item	Unstandardized model			Standardized model		
	Factor loadings	Intercepts	Residual variances	Factor loadings	Intercepts	Residual variances
D'	1.00	2.80	0.49	0.40	3.69	0.84
CV	−0.26	0.26	−0.00	−1.70	5.49	−1.89
ARCES	−0.00	3.45	0.04	−0.01	18.46	1.00
SSRQ	−5.63	113.79	212.64	−0.12	7.75	0.99
MMM-S	−0.03	2.37	0.39	−0.02	3.80	1.00
MAAS	2.15	54.19	130.81	0.06	4.73	1.00
Variance (SA)	0.09			0.95		

Note: ARCES = Log-transformed attention related cognitive errors scale, CV = reaction time variability, D′ = discrimination ability, MAAS = Mindful Attention Awareness Scale, MMM-S = media multitasking- short form, SA = sustained attention latent factor, SSRQ = short self-regulation questionnaire.

3.5.2. Investigating resting vmHRV and sustained attention among participants who report drinking less than one caffeinated beverage habitually

To assess the potential influence of caffeine use among our sample, a subgroup analysis was conducted with repeated sequential linear regressions with resting log-RMSSD and covariates predicting d', CV, ARCES, SSRQ, MMM-S, and MAAS scores in participants who reported consuming less than one caffeinated beverage habitually.

For the regression model predicting discrimination ability (d'), we entered resting log-RMSSD into model one. Resting log-RMSSD ($\beta = -0.29$, $p = .07$) did not account for a statistically significant amount of variance in d' ($R^2 = 0.08$, $F(1, 39) = 3.48$, $p = .07$). Age, gender, BMI, and time of day were entered in model two. After accounting for covariates, resting log-RMSSD ($\beta = -0.33$, $p = .03$, $p_{FDR} = .19$) was not associated with d' (Table 11) after FDR correction.

For the regression model predicting reaction time variability (*CV*), we entered resting log-RMSSD into model one. Resting log-RMSSD ($\beta = 0.04$, $p = .80$) did not account for a statistically significant amount of variance in CV ($R^2 = 0.00$, $F(1, 39) = 0.07$, $p = .80$). Age, gender, BMI, and time of day were entered into model two. After accounting for covariates, resting log-RMSSD ($\beta = 0.10$, $p = .49$) was not associated with CV (Table 11). We did find a significant association between resting log-RMSSD and BMI after FDR correction, in which higher BMI was associated with greater reaction time variability ($\beta = 0.49$, $p < .01$, $p_{FDR} < .05$).

For the regression model predicting attentional errors in daily life (ARCES), we entered resting log-RMSSD into model one. Resting log-RMSSD ($\beta = -0.05$, $p = .77$) did not account for a statistically significant amount of variance in ARCES ($R^2 = 0.00$, $F(1, 39) = 0.09$, $p = .77$). Age, gender, BMI, and time of day were entered into model two. After accounting for covariates, and resting log-RMSSD ($\beta = -0.02$, $p = .91$) was not associated with ARCES (Table 12).

For the regression model predicting self-regulation (SSRQ), we entered the resting log-RMSSD into model one. Resting log-RMSSD ($\beta = -0.03$, $p = .84$) did not account for a statistically significant amount of variance in SSRQ ($R^2 = 0.00$, $F(1, 39) = 0.04$, $p = .84$). Age, gender, BMI, and time of day were entered in the model two. After accounting for covariates, resting log-RMSSD ($\beta = -0.06$, $p = .71$) was not associated with SSRQ (Table 12).

For the regression model predicting media multitasking (MMM-S), we entered resting log-RMSSD into model one. Resting log-RMSSD ($\beta = -0.08$, $p = .60$) did not account for a statistically significant amount of variance in MMM-S ($R^2 = 0.01$, $F(1, 39) = 0.27$, $p = .60$). Age, gender, BMI, and time of day were entered into model two. After accounting for covariates, resting log-RMSSD ($\beta = -0.07$, $p = .65$) was not associated with MMM-S (Table 12).

Finally, we entered the resting log-RMSSD into model one of the regression predicting mindfulness (MAAS). Resting log-RMSSD ($\beta = 0.15$, $p = .36$) did not account for a statistically significant amount of variance in MAAS ($R^2 = 0.02$, $F(1, 39) = 0.87$, $p = .36$). Age, gender, BMI, and time of day were entered into model two. After accounting for covariates, resting log-RMSSD ($\beta = 0.14$, $p = .40$) was not associated with MAAS (Table 12).

Table 11
Regression summary table for the association of resting log-transformed RMSSD and task-based sustained attention within participants who do not habitually consume caffeine.

Variable	D'			CV		
	B	*SE(B)*	β	*B*	*SE(B)*	β
Log-RMSSD	−0.47	0.21	-0.33^{+}	0.01	0.01	0.10
Age	0.08	0.05	0.28	−0.01	0.00	-0.42^{+}
Gender	−0.06	0.24	−0.08	0.02	0.01	0.37
BMI	−0.04	0.02	-0.39^{+}	0.00	0.00	0.49*
Time of Day	−0.20	0.16	−0.19	0.01	0.01	0.10
Model 1 fit	$R^2 = 0.08$, $F(1, 39) = 3.48$, $p = .07$			$R^2 = 0.00$, $F(1, 39) = 0.07$, $p = .80$		
Model 2 fit	$R^2 = 0.25$, $F(5, 35) = 2.38$, $p = .06$			$R^2 = 0.26$, $F(5, 35) = 2.41$, $p = .06$		

Note. $p_{FDR} < .05$* indicates significance after false discovery rate correction (FDR), $p < .05^{+}$ indicates significance before false discovery rate correction (FDR), B = effect size, β = standardized effect size, BMI = body mass index, CV = reaction time variability, D′ = discrimination ability, Log-RMSSD = log-transformed root mean square of the successive differences between normal heartbeats, SE(B) = standard deviation for effect size; time of day = time of day of cognitive assessment.

4. Discussion

In this study, we investigated the relationship between resting vmHRV and sustained attention in the laboratory using a neuropsychological assessment and daily life using self-report questionnaires. To assess the validity of the gradual-onset continuous performance task (gradCPT), we compared performance measures for the first half of testing to the second half of testing (H_1 and H_2). Next, we aimed to assess if participants exhibited a decline in vmHRV during cognitive testing relative to resting baseline (vagal withdrawal) to validate autonomic demands of the gradCPT (H_3). Finally, we conducted frequentist, Bayesian, and structural regression analyses predicting task-based (H_4 and H_5) and dispositional measures of sustained attention (H_6 - H_9).

When assessing time-on-task decrements on the gradCPT using our primary outcome measures of discrimination ability (d') reaction time variability (CV), we found significant time-on-task performance decrements, demonstrated by a decline in discrimination ability (d') and an increase in reaction time variability (CV). This is consistent with previous work demonstrating a reliable decline in performance as a function of time on task (Esterman et al., 2013; Esterman et al., 2014).

Contrary to our expectations, vagally mediated heart rate variability (vmHRV) was significantly higher during cognitive testing than the resting baseline (H_3). This finding is inconsistent with previous work that has found that participants exhibit vagal withdrawal during cognitively demanding tasks relative to resting baseline (Manser et al., 2021). Several factors may play a role in this unexpected finding. First, the self-regulatory effort necessary to complete the gradCPT may have

Table 12
Regression summary table for the association of resting log-transformed RMSSD and dispositional sustain attention within participants who do not habitually consume caffeine.

Variable	ARCES			SSRQ			MMM-S			MAAS		
	B	*SE(B)*	β	*B*	*SE(B)*	β	*B*	*SE(B)*	β	*B*	*SE(B)*	β
Log-RMSSD	−0.01	0.05	−0.02	−1.53	4.01	−0.06	−0.08	0.17	−0.07	2.39	2.78	0.14
Age	−0.01	0.01	−0.21	0.80	0.98	0.16	0.01	0.04	0.02	−0.10	0.68	−0.03
Gender	0.09	0.06	0.53	−7.53	4.71	−0.52	0.06	0.20	0.11	−1.77	3.26	−0.18
BMI	−0.00	0.00	−0.08	−0.00	0.34	−0.00	0.02	0.01	0.25	−0.08	0.24	−0.06
Time of Day	0.03	0.04	0.12	−3.54	3.10	−0.19	0.13	0.13	0.17	−2.41	2.14	−0.19
Model 1 fit	$R^2 = 0.00$, $F(1, 39) = 0.09$, $p = .77$			$R^2 = 0.00$, $F(1, 39) = 0.04$, $p = .84$			$R^2 = 0.01$, $F(1, 39) = 0.27$, $p = .60$			$R^2 = 0.02$, $F(1, 39) = 0.87$, $p = .36$		
Model 2 fit	$R^2 = 0.15$, $F(5, 35) = 1.20$, $p = .33$			$R^2 = 0.13$, $F(5, 35) = 1.05$, $p = .40$			$R^2 = 0.10$, $F(5, 35) = 0.80$, $p = .56$			$R^2 = 0.07$, $F(5, 35) = 0.52$, $p = .76$		

Note. ARCES = log-transformed attention related cognitive errors scale, B = effect size, β = standardized effect size, BMI = body mass index, log-RMSSD = log-transformed root mean square of the successive differences between normal heartbeats, MAAS = Mindful Attention Awareness Scale, MMM-S = media multitasking-short form, SE(B) = standard deviation for effect size, SSRQ = short self-regulation questionnaire, time of day = time of day of cognitive assessment.

increased vmHRV during task completion relative to rest. This theory is consistent with previous studies in which participants exhibit increased vmHRV when practicing behavioral regulation (Butler et al., 2006; Denson et al., 2011; Segerstrom and Nes, 2007). Second, the gradCPT stimuli consist of neutral grayscale city and mountain scenes, which participants most likely perceived as non-threatening. Previous work suggests that threatening and emotional stimuli decrease vmHRV to a greater extent than neutral stimuli (Van Der Ploeg et al., 2017). Grayscale imagery has also been found to increase vmHRV when used as a cue during cognitive assessment, while red imagery significantly decreased vmHRV (Elliot et al., 2011). Finally, we told participants encouraging instructions during task practice and familiarization (i.e., the task was intended to be a challenge and to try their best) to encourage task compliance. This ultimately led to excellent task compliance, but these instructions may have contributed to a calming and non-threatening environment for participants. The exploratory analysis did confirm that participants exhibited a significant decrease in vmHRV during the second half of the gradCPT compared to the first half. This suggests that participants did experience vagal withdrawal during the task despite the lack of vagal withdrawal relative to baseline. This is consistent with previous work finding that changes in vmHRV are sensitive to sustained attentional demands (Luque-Casado et al., 2016).

After validating our cognitive assessment (H_1 and H_2) and exploring changes in vmHRV from rest to task (H_3), we then conducted our linear regression analyses predicting task-based (H_4 and H_5) and dispositional self-report measures of sustained attention (H_6–H_9). Counter to our predictions, we did not find evidence to support an association between resting vmHRV and d' (H_4) or CV (H_5) across frequentist and Bayesian linear regressions. Further, we did not find evidence to support an association between resting vmHRV and dispositional factors related to sustained attention, specifically self-reported attention errors (H_6), mindfulness (H_7), self-regulation (H_8), or media-multitasking (H_9). Findings were consistent with and without the inclusion of covariates accounting for age, gender, BMI, and time of day of assessment. Findings were also consistent in exploratory analyses of frequentist linear regressions predicting task-based and dispositional measures of SA conducted in a sub-group of participants who reported not consuming caffeine habitually.

Using structural equation models, we found that resting vmHRV was not a significant predictor of a unitary latent variable representing task-based and dispositional factors related to sustained attention (H_4–H_9). Resting vmHRV was also not a significant predictor of task-based (H_4, H_5) or dispositional (H_6–H_9) latent measures of sustained attention in our two-factor model of sustained attention. Global and local model fit indices were very poor for the unitary model of SA, while the two-factor model separating task-based and survey-based measures exhibited good model fit. This suggests that task-based and survey-based measures were independent in our sample.

Our hypothesis linking between resting vmHRV and sustained attention relied heavily on the neurovisceral integration model (Thayer and Lane, 2009) and previous behavioral studies in a similar sample (Siennicka et al., 2019; Spangler et al., 2018; Williams et al., 2016). The neurovisceral integration model has been the theoretical pillar for studies linking resting vmHRV to executive functioning (Forte et al., 2019), an ability closely tied to sustained attention (Fisher and Kloos, 2016). There is considerable evidence across neuroimaging and neuropharmacology studies linking resting vmHRV to activity in the prefrontal cortex, the brain regions most closely linked to executive function (Matusik et al., 2023; Thayer et al., 2012; Thayer and Lane, 2009). While prefrontal function is integral to successful SA, previous work has found several additional brain regions to play a crucial role in individual differences in SA that have not been implicated in previous work with vmHRV (Fortenbaugh et al., 2018; Langner and Eickhoff, 2013; Matusik et al., 2023; Mitko et al., 2019). Neural correlates of SA not implicated in neuroimaging studies of vmHRV include the intraparietal sulcus, temporal-parietal junction, intraparietal sulci, middle occipital gyrus, temporal occipital junction, posterior cingulate cortex (PCC), the left lateral parietal cortex, and the visual cortex (Fortenbaugh et al., 2018; Langner and Eickhoff, 2013; Matusik et al., 2023; Mitko et al., 2019). Further, previous work suggests the neural correlates of vmHRV appear predominantly localized spatially in the prefrontal cortex (Matusik et al., 2023), while SA relies on complex networks of brain regions across the brain (Fortenbaugh et al., 2018; Mitko et al., 2019). The utilization and coordination of diverse brain regions in sustained attention may limit the applicability of neurovisceral integration to sustained attention more than previously thought.

The performance-based studies utilized in our justification for a link between task-based SA and resting vmHRV (H_4 and H_5) demonstrated an association between higher resting vmHRV with fewer attentional lapses (Spangler et al., 2018), better attentional maintenance (Siennicka et al., 2019), and a more consistent reaction time on an attention task (Williams et al., 2016). One key difference with previous work is our use of a validated measure of sustained attention in the current study. Previous studies found compelling evidence of a link between resting vmHRV and aspects of sustained performance derived from tasks designed to measure inhibitory control (Spangler et al., 2018), selective attention (Williams et al., 2016), visual scanning, and processing (Siennicka et al., 2019). These differences in task characteristics may play a pivotal role in the discrepancy between previous performance-based findings and the current study.

Our hypotheses linking resting vmHRV and self-reported factors related to sustained attention in daily life (H_6 - H_9) were based on previous studies demonstrating a relationship between higher resting vmHRV and better behavioral regulation (Holzman and Bridgett, 2017; Thayer and Lane, 2000, 2009). In the current study, we utilized self-report measures to assess abilities related to both sustained attention and, more broadly, behavioral regulation, specifically attentional errors, mindfulness, media multi-tasking, and self-regulation. The reliance on self-report questionnaires is a critical difference between the current work and previous studies that primarily relied on cross-sectional lab-based paradigms that require behavioral regulation (Holzman and Bridgett, 2017), as well as intervention studies aimed to increase vmHRV and improve behavioral regulation with breathing and mindfulness techniques (Burg and Wolf, 2012; Lehrer, 2022). The self-report questionnaires may have captured perceptions of abilities related to sustaining attention rather than quantifying actual function in daily living. This would be consistent with previous work that suggests the perception of cognitive abilities does not correlate with objective cognitive ability in healthy adults (Buchanan, 2016).

This study has several limitations. First, we did not give participants instructions regarding caffeine and exercise abstention the day of the study, factors that may situationally alter resting vmHRV values (Quintana et al., 2016). However, when we restricted analyses to a subset of participants who reported abstaining from caffeine, the lack of association between vmHRV and SA performance persisted. Future work should consider guidelines and screening criteria established in previous work (Quintana et al., 2016). Second, the study was conducted with young adults, and its findings may not generalize to middle-aged or older adults. This is because age moderates the relationship between vmHRV and behavioral regulation, such that the association becomes stronger with older age (Holzman and Bridgett, 2017). Third, we relied on self-report measures of attentional errors, self-regulation, media-multitasking, and mindfulness. Previous work suggests that self-report measures of behavioral regulation are more closely linked to personality traits rather than objective function (Buchanan, 2016).

5. Conclusion

This is the first study to assess the association between resting vmHRV and a validated measure of sustained attention. This is also the first study to assess the association between resting vmHRV and self-report measures related to dispositional sustained attention (i.e., attentional errors, self-regulation, media multi-tasking, and mindfulness) in a comprehensive fashion. These self-report measures assess aspects of behavioral control closely linked to resting vmHRV through neurovisceral integration (Thayer and Lane, 2009). Our null findings regarding resting vmHRV, task-based sustained attention, self-report measures of attentional errors, self-regulation, media multi-tasking, and mindfulness are novel and important to the field. Previous work has found publication status to be a significant moderator in the relationship between resting vmHRV and behavioral regulation studies (Holzman and Bridgett, 2017), following a troubling trend found across psychological sciences known as "the file drawer effect," in which null results are primarily rejected by journals in favor of positive findings (Wagner, 2022). Future studies are warranted to replicate the current work.

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CRediT authorship contribution statement

Thomas Wooten: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Validation, Writing – original draft, Writing – review & editing. **Michael Esterman:** Writing – review & editing, Conceptualization. **Tad T. Brunyé:** Writing – review & editing, Conceptualization. **Holly A. Taylor:** Conceptualization, Writing – review & editing. **Nathan Ward:** Conceptualization, Supervision, Writing – review & editing.

Data availability

Data is available on OSF. The link of which is in the manuscript several times and can be found here: https://osf.io/8cqhv/.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ijpsycho.2024.112298.

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