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EXAMINING BETWEEN AND WITHIN-PERSON RELATIONSHIPS BEWEEN PARASYMPATHETIC NERVOUS SYTEM ACTIVITY AND COGNITIVE REGULATION: EFFECTS OF TASK TYPE AND RANGE CORRECTION

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ABSTRACT

Theories of how the activity of the parasympathetic nervous system (PNS) contributes to cognitive regulation have been supported by empirical findings linking heart rate variability (HRV) to performance on cognitive challenge tasks. However, these studies have primarily compared baseline levels of HRV to measures of task performance. Theories that propose a link between PNS activity and cognitive regulation may be better tested by assessing concurrent relationships between HRV and measures of task performance. In addition, existing research has primarily relied on a set of cognitive challenge tasks which require participants to provide rapid behavioural responses. Tasks that allow more time for deliberation prior to providing a behavioural response may tax cognitive regulation in a unique way. Specifically, the relationships between PNS activity and brain activity elaborated in Neurovisceral Integration Theory suggest that lower PNS activity may facilitate performance on rapid response tasks, while performance on deliberative tasks may be facilitated by higher PNS activity. This dissertation will add to the existing literature by studying the relationship between PNS regulation and cognitive regulation, utilizing measures of HRV taken concurrently with the performance of both a rapid responding and deliberative task. Studies of how the PNS contributes to cognitive regulation have also tended to utilize between-person analysis methods. This dissertation will build on existing findings by utilizing both within and between-person approaches to studying the contribution of PNS activity to cognitive regulation. Specifically, in addition to between-person analyses, multilevel modelling approaches will be used to examine within-person associations of intra-individual variability in HRV and task performance.

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Introduction

Contributions of the parasympathetic nervous system to cognitive regulation

The contribution of the parasympathetic nervous system (PNS) to cognitive regulation has received increasing attention within psychophysiology, thanks in large part to two functional-anatomical theories, Polyvagal Theory (Porges, 1995; Porges, 2007) and Neurovisceral Integration Theory (Thayer & Lane, 2000; Thayer & Lane, 2009). These theories propose that the PNS (specifically the myelinated branch of the vagus nerve) is a major contributor to the more general process of self-regulation (see Nigg, 2017), due in large part to bidirectional interactions of the PNS and central nervous system structures that underlie cognitive regulation, particularly the prefrontal cortex and the amygdala. Cognitive regulation refers to the ability of individuals to adjust their cognitive state to meet changing environmental demands and shifts in prefrontal and amygdala activity are thought to be a major biological substrate of this process (Arnsten, 2009; Thayer & Lane, 2009). Under normal conditions (i.e., absent severe threats to wellbeing or extreme emotional distress), the prefrontal cortex maintains inhibitory control over the amygdala, such that reductions in prefrontal activity lead to concurrent increases in amygdala activity. Evidence suggests that measures of PNS activity may act as an indirect measure of the relative balance between prefrontal and amygdala activity (Porges, 2007; Arnsten, 2009; Thayer & Lane, 2009), and thus may provide information about an individual's cognitive state. PNS regulation - meaning functional changes in PNS activity that occur in response to the changing needs of an organism – has long been considered to co-occur with changes in brain activity that underlie cognitive regulation (Bennaroch, 1993; Fox, 1994; Porges, Doussard-Roosevelt, & Maiti, 1994; Wilson & Gottman, 1996). In this dissertation, I will examine the relationship between these two regulatory processes in the context of two cognitive challenge tasks that place different demands on cognitive regulation.

Relationship between Cognitive and PNS regulation

Cognitive regulation is defined here as changes in an individual's cognitive state that occur in response to changing cognitive demands. Cognitive state is believed to be an emergent property of central nervous system activity (Arnsten, 2009; Evans & Stanovich, 2013), such that the shifts between different cognitive states which characterize cognitive regulation should be evidenced to some extent by changing patterns of brain activity. Successful cognitive regulation should match an individual's cognitive state to their current needs, such that task performance may serve as a marker of cognitive regulation in the context of a cognitive challenge task. Importantly, the balance of prefrontal and amygdala activity that is thought to be indexed by PNS activity is also thought to contribute to different cognitive states which may facilitate or inhibit task performance depending on the context (Evans & Stanovich, 2013). Specifically, when cognitive demands require quickly identifying and responding to simple features of sensory stimuli, it should be expected that lower prefrontal and higher amygdala activity should facilitate better task performance. This is because the prefrontal cortex is involved in higher-order cognitive processes which unfold more slowly. Relying on this slower acting system in the context of significant time pressure may inhibit performance. In contrast, other cognitive challenge tasks require higher-order deliberative processes that take longer to unfold and rely on higher levels of activation in the prefrontal cortex and subsequent decreases in amygdala activity (Posner & Snyder, 1975; Posner, 1978; Evans & Stanovitch, 2013).

Neurovisceral Integration theory proposes that the patterns of brain activity that accompany different cognitive states co-occur with low and high levels of PNS activity (Thayer & Lane, 2000; Thayer & Lane, 2009). A heuristic model summarizing how PNS activity is thought to relate to patterns of brain activity (and thus cognitive state) can be seen in Figure 1 below. This figure depicts both the central theoretical proposition of the current

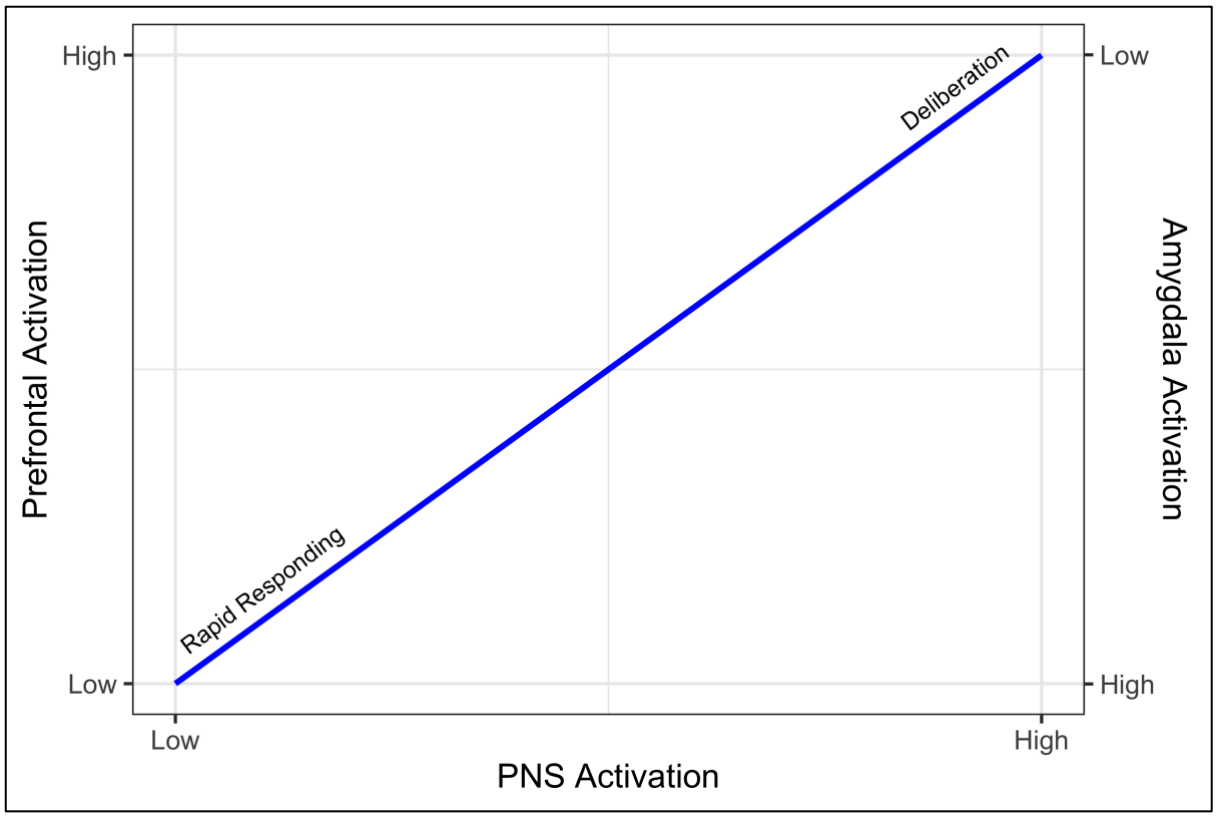

Figure 1. Heuristic model showing the relationship between PNS, prefrontal, and amygdala activation presented in Neurovisceral Integration Theory. The prefrontal cortex exerts inhibitory control over the amygdala, such that increased prefrontal activation leads to decreased amygdala activation, and decreased prefrontal activation leads to increased amygdala activation via disinhibition. The PNS in turn exerts an excitatory effect on the prefrontal cortex, such that increasing PNS activity is believed to correspond with both increases in prefrontal activation and concomitant decreases in amygdala activation. The psychophysiological state which results from the pattern of activation on the left side of the plot (low PNS activation, low prefrontal activation, high amygdala activation) is expected facilitate better task performance when rapid responding is integral to performance. The psychophysiological state which results from the pattern of activation on the right side of the plot (high PNS activation, high prefrontal activation, low amygdala activation) is expected facilitate better task performance on tasks that require deliberation.

dissertation, as well as one of the primary hypotheses. Movement along the x-axis of this figure is meant to depict the changes in PNS activation that make up the process of PNS regulation. Likewise, movement along the diagonal line running through the center of this figure depicts the shifts between different cognitive states that comprise cognitive regulation. This is undoubtedly an oversimplification of the relationship between PNS and cognitive

regulation but expresses the basic conceptual premise that PNS regulation and cognitive regulation should be expected to co-occur.

Many studies have examined the relationship between PNS and cognitive regulation using measures of heart rate variability (HRV), a well validated physiological index of PNS activity (Cacioppo, 1994; Porges, 2007; Thayer, Ahs, Fredrikson, Sollers III, Wager, 2012), and various task performance measures, with the assumption that more successful cognitive regulation will be accompanied by better task performance. Such studies have provided considerable evidence that PNS regulation contributes to cognitive regulation (see Forte, Favieri, & Casagrande, 2019 for a review), although the existing evidence base is limited in terms of its ability to falsify or verify the predictions derived from the conceptual model depicted in Figure 1 based on three factors. First, the relationships between PNS activity, brain activity, and cognitive state are proposed to occur concurrently, but the association between HRV and task performance is often tested using HRV measures taken prior to, rather than during, task performance. Second, many studies have found a relationship between HRV and performance measures on rapid-responding cognitive challenge tasks, but very few have assessed the relation between HRV and performance using deliberative cognitive challenge tasks. And third, the majority of studies have examined associations between HRV and task performance at the between-person level. While many between-person associations between HRV and task performance have been found, PNS regulation and cognitive regulation are both intra-individual processes. This dissertation will examine the relationship between HRV, an index of PNS regulation, and cognitive task performance, an index of cognitive regulation, while addressing each of these three gaps in our current knowledge.

Operationalizing PNS Regulation in Cognitive Challenge Contexts

Many studies have used HRV to study changes in PNS activity that occur in response to changes in cognitive demands across experimental conditions, which can be considered a

measure of PNS regulation. Such studies have generally found that HRV levels are lower during the performance of a cognitive challenge task relative to a pre-task baseline (Porges & Raskin, 1969; Backs, Ryan, & Wilson, 1994; Gianaros, van der Veen, & Jennings, 2004; Muth, Moss, Rosopa, Salley, & Walker, 2012; Overbeek, Boxtel, & Westerink, 2014; Park, Vasey, Van Bavel, & Thayer, 2014; Byrd, Reuther, McNamara, DeLucca, & Berg, 2015; Hu, Lamers, de Gues, Penninx, 2016), suggesting that PNS regulation does occur concurrently with task performance. These studies have helped to establish that PNS regulation occurs in response to cognitive challenge but did not test whether HRV measures were related to measures of task performance. Studies that have examined the relationship between HRV measures and task performance have generally relied on three different HRV measures, either on their own or in combination. The most commonly used of these measures is baseline HRV, typically measured prior to task performance. Findings that baseline HRV is related to task performance measures are reviewed below, although as discussed above these findings do not relate to the concurrent relationship between HRV and performance. Two other HRV measures taken concurrently with task performance are HRV reactivity and on-task HRV. Findings regarding the relationship between PNS regulation and cognitive regulation appear to depend to some extent on the specific HRV measures that are used to operationalize PNS regulation. The following sections will summarize the literature regarding how baseline HRV, HRV reactivity, and on-task HRV relate to measures of cognitive task performance.

Baseline HRV. Many studies rely on between-person differences in performance on cognitive tasks to operationalize between-person differences in cognitive regulation. A consistent finding relating PNS activity so such task performance measures have been that higher levels of HRV taken during a pre-task baseline period were associated with better task performance (Suess et al., 1994; Hansen, Johnsen, & Thayer, 2003; Segerstrom & Nes, 2007; Staton, El-Sheikh, & Buckhalt, 2009; Mathewson et al., 2010; Marcovitch et al., 2010; Gillie,

Vasey, & Thayer, 2013; Capuana et al., 2014; Sulik, Eisenberg, Spinrad, & Silva, 2015; Williams et al., 2016; Colzato & Steenbergen, 2017; Colzato et al., 2018; Zeki et al., 2018; Ottavani et al., 2018; Williams et al., 2019; Spangler & McGinley, 2020). Because these studies cite baseline HRV as a measure of PNS regulation, these findings are interpreted as evidence that PNS regulation contributes to successful cognitive regulation. However, the use of a pre-task baseline as a measure of PNS regulation is at odds with the concept of regulation as a dynamic process that unfolds over time (Carver & Scheier, 1982; Cole et al., 2004; Bell & Deater-Deckard, 2007). This is not to suggest that baseline measures of HRV are unrelated to the process of PNS regulation, but simply suggests that baseline measures on their own are not a measurement of regulation in-and-of themselves. Several authors have suggested that baseline HRV may represent an index of an individual's *capacity* for regulation (Porges et al., 1994; Calkins 1997; Segerstrom & Nes, 2007), often based on the view that PNS regulation specifically involves reductions in PNS activity, also known as PNS withdrawal (Porges, 2007). This framework proposes that individuals with higher levels of baseline HRV may be more capable of utilizing PNS withdrawal as a psychophysiological strategy for coping with cognitive challenge, in order to explain why higher baseline HRV has been found to correlate with better task performance.

HRV Reactivity. HRV reactivity is typically calculated by measuring HRV during task performance, and then subtracting baseline HRV to arrive at a measure of change between the baseline and on-task conditions. Because reactivity measures quantify change, they are more directly related to the concept of regulation at a conceptual level than static measures like baseline HRV. Several studies have found that HRV reactivity tends to be negative on average (Suess et al., 1994; Hansen et al., 2003; Segerstrom & Ness, 2007; Kimhy et al., 2013), suggesting that PNS activity tends to decrease during task performance. While these studies did not examine the association between HRV reactivity and task

performance measures, other studies have found that more negative HRV reactivity was associated with better task performance (Duschek et al., 2009; Mathewson et al., 2010; Capuana et al., 2014; Giuliano, Roos, Farrar, & Skowron, 2018). One explanation for these findings is that reductions in PNS activity lead to increases in physiological arousal (such as an increase in heart rate), which in turn directs metabolic resources towards attentional and behavioral systems that facilitate engagement with environmental demands (Backs, Ryan, & Wilson, 1994; Porges, 1995). This explanation is consistent with Polyvagal Theory, which emphasizes the role of peripheral arousal in how PNS regulation relates to cognitive regulation.

Others have argued that HRV reactivity should be *positively* related to cognitive task performance based on the positive association between PNS activity and prefrontal activation laid out in Neurovisceral Integration Theory. This point has been made in the context of findings that increases in HRV predicted better task performance (Elliot, Payen, Brisswalter, Cury, & Thayer, 2011; Giuliano, Gatzke-Kopp, Roos, & Skowron, 2018). While findings that both negative and positive HRV reactivity predict better task performance may appear contradictory, they are consistent with the heuristic model depicted in Figure 1 once task type has been considered. Studies which found negative HRV reactivity to predict better task performance have primarily utilized rapid-responding tasks, where it is expected that performance will be facilitated by lower PNS activity. Studies finding that positive reactivity predicts better performance have come from tasks that allowed individuals sufficient time to engage in deliberation prior to providing responses, where it is expected that performance will be facilitated by higher PNS activity. In other words, task type may moderate the association between HRV reactivity and cognitive task performance. This dissertation will directly test this hypothesis, utilizing HRV reactivity and task performance data taken during both a rapid responding and deliberative cognitive challenge task.

While both baseline HRV and HRV reactivity have been found to be independently related to cognitive task performance, conceptual arguments as well as empirical evidence suggest that PNS regulation may be best operationalized using a combination of both measures (Hinnant & El-Sheikh, 2009; Cribbet, Williams, Gunn, & Rau, 2011; Yaroslavsky, Bylsma, Rottenberg, & Kovacs, 2013; Sulik, Eisenberg, Spinrad, & Silva, 2015). For example, Polyvagal Theory proposes that successful PNS regulation is characterized by both higher levels of baseline HRV and negative HRV reactivity in response to increased environmental demands (Porges, 1995; Porges, 2007). Statistically, the combined relationship of baseline HRV and HRV relativity is often examined using regression to test for a significant interaction between the two HRV measures in predicting some psychological outcome. Models testing for an interaction between baseline HRV and HRV reactivity have found that higher baseline HRV combined with negative HRV reactivity to predict fewer externalizing symptoms in children (Hinnant & El-Sheikh, 2009), greater maintenance of positive affect during a stress task in an undergraduate sample (Cribbet et al., 2011), and fewer depression symptoms in an adult sample (Yaroslavsky et al., 2013). This dissertation will add to the existing literature by examining the relationship between PNS regulation – as measured by baseline HRV, HRV reactivity, as well as their interaction – with cognitive regulation, as measured by task performance.

On-Task HRV. While an increasing number of studies utilize both baseline and HRV reactivity measures, very few studies examine the association between cognitive regulation and HRV measured during cognitive task performance. The relative lack of interest in how on-task HRV relates to cognitive regulation is highlighted by the fact that many studies only measure HRV during a baseline period but not during task performance (Gille, Vasey, & Thayer, 2003; Britton et al., 2008; Williams et al., 2016; Colzato & Steenbergen, 2017; Colzato et al., 2018; Ottaviani et al., 2018). Among two studies using on-task HRV measures

to predict cognitive task performance in healthy adults, one found that *lower* on-task HRV was associated with better performance (Duschek et al., 2009), consistent with findings that negative HRV reactivity predicted better performance. Another found no significant association between on-task HRV and task performance (Mathewson et al., 2010). Given the scarcity of these studies, additional evidence is required to determine whether on-task HRV levels during a cognitive challenge task are related to task performance and, by extension, cognitive regulation. However, conceptual models of psychophysiology suggest that physiology continuously supports ongoing behavior (Beauchaine, Gatzke-Kopp, & Mead, 2007), which may manifest as a concurrent relationship between physiology and task performance.

More specific to HRV, the PNS is able to engage in regulation at a rapid (< 1 second) timescale, owing to the fact that the vagal fibers that facilitate PNS regulation are myelinated (Berger, Saul, & Cohen, 1989; Grossman & Taylor, 2007; Porges, 2007; Thayer & Lane, 2009). Thus, the association between PNS regulation and cognitive regulation likely unfolds in real time. In this dissertation, measures of on-task HRV will be used in addition to baseline and reactivity measures and examined for a relationship with cognitive regulation. While the use of a static measure of HRV to operationalize PNS regulation is at odds with the view of regulation as a dynamic process outlined above, the fact remains that the majority of the evidence linking HRV with task performance rely on such a static measure (baseline HRV). Using both baseline and on-task HRV to predict task performance will help to establish whether general trait-like differences in HRV level are what contribute to between person differences in cognitive regulation, or if baseline measures are uniquely predictive.

The Importance of Task Type

Many of the findings which relate HRV to performance on cognitive challenge tasks come from studies which require rapid behavioral responses. For example, participants were

given a maximum of 2500 ms to respond to individual trials of the Stop-change task (Colzato & Steenbergen, 2017), 2000 ms for the Task switching paradigm (Colzato et al., 2018), 750 ms on a Flanker Task (Williams, Thayer, & Koenig, 2016), and 600 ms on a Stroop task (Capuana et al., 2014). Other tasks do not specifically limit the length of each trial, but encourage participants to respond to stimuli as quickly as they can. This was the case for the tasks used by Hansen and colleagues (2003) and Ottaviani and colleagues (2019), but despite an explicit limit on trial length these tasks elicited normal behavioral responses of less than one second per trial. The "Test d2" used by Duschek and colleagues (2009) did not involve discrete trials, but instead presented participants with 14 rows containing 47 letters each and gave them 20s per row to identify as many target stimuli as they could. Despite these differences, all of these tasks are designed to put participants under time pressure, such that responding quickly is critical to good performance. In addition to the time pressure, these tasks also require participants to choose between a small number of behavioral responses.

It is important to consider whether findings relating HRV to task performance illustrate a general pattern of association between PNS activity and cognitive regulation, or whether these findings are instead specific to the kinds of rapid-response tasks that have typically been employed. A full test of the Neurovisceral heuristic model depicted in Figure 1 requires examining the relationship between PNS regulation and cognitive regulation in the context of a more deliberative cognitive task in addition to the rapid-responding tasks that have traditionally been used. Findings from studies that measured HRV concurrently with task performance are consistent with the notion that PNS regulation manifests differently across different types of tasks. For example, Overbeek and colleagues (2014) found that performance of a cognitively demanding working memory task was associated with reductions in HRV, but that no significant change in HRV level occurred during a low-demand perceptual attention task. However, this between-task difference in HRV reactivity

was attributed to the fact that one task was cognitively demanding (thus inducing a regulatory response) while the other was not. Testing the heuristic model presented in Figure 1 requires differentiating patterns of PNS regulation across tasks that differ in the nature of their cognitive demands (rapid-responding vs. deliberation), rather than between high and low-demand conditions.

A more relevant finding to the current discussion is provided by Byrd and colleagues (2015), who found that both a Stroop and N-back task, which demand rapid behavioral responses, were associated with reductions in HRV, but that a third task that was self-paced and required planning and deliberation (Tower of London task) was not associated with changes in HRV on average. Furthermore, although the more deliberative task was not associated with a significant increase in HRV on average, an examination of the means and standard deviations of HRV reactivity for each of the tasks suggest that the majority of individuals had decreases in HRV during the two rapid-responding tasks, but an increase in HRV during the more deliberative task. This pattern of findings is consistent with the idea that PNS regulation during cognitive challenge may be characterized by decreases or increases in HRV, depending on the nature of the challenge task.

The two studies cited above provide evidence that HRV reactivity differs between different types of tasks. However, neither of these studies assessed whether between-person differences in HRV reactivity were related to task performance. Two studies which did test for an association between HRV reactivity and task performance suggest that PNS regulation may aid cognitive regulation in a way that is dependent on the nature of the cognitive challenge. Duschek and colleagues (2009) found that both HRV reactivity and on-task HRV were *negatively* associated with performance on the "Test d2", which requires rapid, simple behavioral responses under time pressure. A study by Giuliano and colleagues (2017) found instead that HRV reactivity was *positively* associated with performance on a working memory

task (although this effect was moderated and only found among participants with lower levels of baseline sympathetic activity). Trials on the task used in this study required participants to view two images of an array squares of different colors, presented one after the other, and identify whether the color of a specific square had changed between the first and second presentation. Importantly, participants were allowed to take as much time as they wanted on each trial. The authors suggested positive association between HRV reactivity and performance may be due to the lack of time pressure, allowing for greater recruitment of deliberative prefrontal systems which operate too slowly to facilitate performance on rapid response tasks (Thayer & Lane, 2009). These two findings are consistent with the heuristic model presented in Figure 1, although assessing the relationships between HRV and task performance within a single sample that performed both a rapid-responding and deliberative cognitive challenge task would allow for a more direct assessment of whether task type moderates the association between PNS and cognitive regulation.

Hypothesized Relationships Between HRV Measures and Task Performance

The current dissertation will utilize baseline, reactivity, and on-task measures of HRV and examine their relationship with cognitive regulation during both a rapid-responding and deliberative cognitive task. As a first step, the independent relationship between each of these measures and task performance will be examined. Based on existing evidence, it is expected that baseline HRV measures will be positively associated with performance and each of the cognitive challenge tasks. Furthermore, it is hypothesized that the relationship between both HRV reactivity and on-task HRV and task performance will be moderated by task type. For the rapid-responding task, it is expected that lower HRV during task performance will predict better performance. This may manifest as either HRV reactivity or on-task HRV having a negative association with performance measures, or potentially both as was found in one study (Duschek et al., 2009). For the deliberative task, it is expected that higher HRV will

predict better performance. This may manifest as HRV reactivity and/or on-task HRV having a *positive* relationship with performance. Potential moderation of the relationship between HRV reactivity and task performance by baseline HRV will also be examined. It is hypothesized that there will be evidence of such moderation on each cognitive task. For the rapid-responding task, it is hypothesized that higher baseline HRV will be associated with a stronger *negative* relationship between HRV reactivity and task performance, based on the assumption that individuals with higher levels of pre-task PNS activity are better situated to benefit from PNS withdrawal. For the deliberative task, it is hypothesized that lower baseline HRV will be associated with a stronger *positive* relationship between HRV reactivity and task performance, based on the assumption that individuals with lower levels of pre-task PNS activity are better situated to benefit from PNS augmentation.

Quantifying HRV Change to Operationalize PNS Regulation

The hypothesized relationships between PNS and cognitive regulation expressed in the above sections are primarily based on findings from studies of between-person relationships. While such studies have greatly contributed to the understanding of the psychophysiology of PNS regulation, studies of within-person patterns of change over time may offer unique information (Nesselroade & Ram, 2004). Within-person analytical approaches that quantify change across multiple time points are also more in line with the conception of regulation as a dynamic process discussed above (Carver & Scheier, 1982; Cole et al., 2004; Bell & Deater-Deckard, 2007). While there are many approaches to quantifying change, this dissertation will examine two that have been applied to HRV data for the purposes of modeling PNS regulation. First, the use multilevel modelling approaches (see Snijders & Boskers, 1999) is increasingly common within psychology, and several recent studies have used this approach to study patterns of intra-individual variability in HRV (Muth et al., 2012; Giuliano et al., 2017; Gatzke-Kopp & Ram, 2018; Gatzke-Kopp, Benson, Ryan,

& Ram, 2020; Schmalenberger et al., 2019; Schmid & Thomas, 2021; Weissman & Mendez, 2021). Example of intra-individual variability in HRV are presented in Figure 2, which shows second-by-second HRV data from a single individual measured across multiple contexts as part of the current study. The variability in HRV that occurs within a task condition that is apparent in Figure 2 is normally removed in between-person studies by taking a single measure of on-task HRV across the entire task. In contrast, a within-person approach allows for the relationship between variability in HRV and measures task performance to be assessed, in order to determine whether PNS regulation contributes to cognitive regulation.

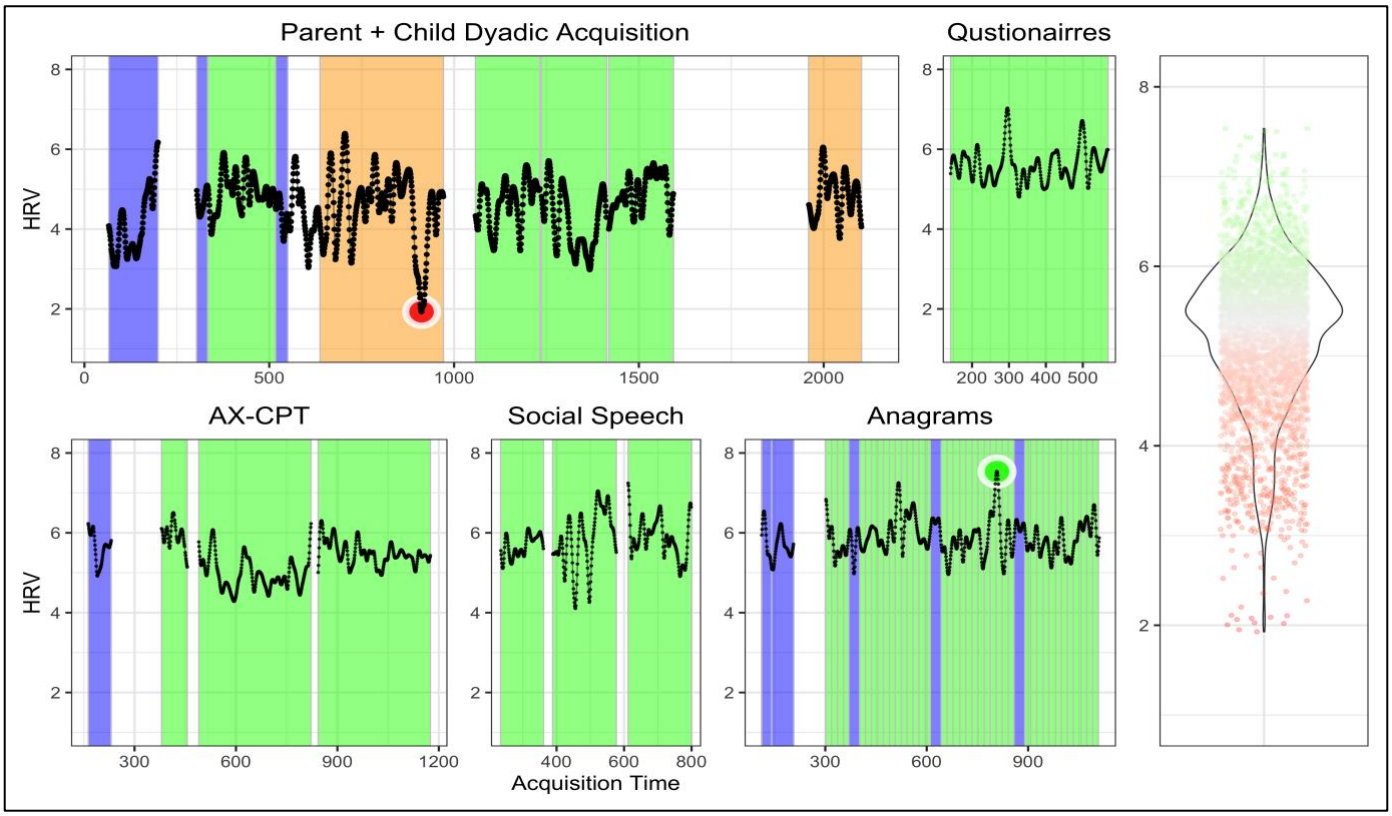

Figure 2. HRV Data from a single individual across multiple measurement periods and task types. Within-person minimum and maximum values are highlighted with a red and green circle. The five time-series plots represent the five different data acquisition periods that occurred over the lab visit. Background colors indicate different measurement contexts, with blue representing baseline periods, green represent periods of task performance, and orange representing semi-structured "free play" periods where parents interacted with their children. The violin plot on the right shows the within-person distribution of HRV values across all of the measurement periods displayed in the time series plots.

An alternative approach to studying within-person variability in PNS activity is to quantify the extent to which an individual's HRV varies over time using a measure of "net intra-individual variability" (Ram & Gerstorf, 2009). For example, the HRV data that is depicted in Figure 2 could be summarized by the standard deviation of HRV, or the total range of HRV values. Such measures express information about intra-individual variability in the form of a between-person variable. For example, the maximum and minimum HRV values observed across tasks are highlighted in Figure 2 using green and dots respectively. The difference between these two values may provide a measure of an individual's capacity for engaging in PNS regulation, such that higher values reflect a more "flexible" PNS that is better able to adapt to changing demands (Friedman, 2007). Such a between-person measure of intra-individual variability can be used analytically in a similar way to more traditional measures of HRV level or reactivity. This dissertation will utilize both the multilevel modeling and net intra-individual variability approaches to examine the relationship between PNS regulation and cognitive regulation.

Before exploring approaches to quantifying change in HRV it is important to clarify what the relevant timescales of change are. First, there is the timescale over which changes in PNS activity are thought to occur. Theories of PNS regulation emphasize the fact that PNS activity can be rapidly adjusted on the timescale of milliseconds, given the fast conduction velocity of myelinated vagal fibers (Fagraeus & Linnarsson, 1976; Rowell, 1986). However, there is also the timescale at which HRV can be measured. HRV presents a unique measurement challenge, given that it is a measure of *variability*, specifically variability in the length of successive heartbeats. This fact limits the temporal resolution with which HRV could be calculated. While mathematically variability could be calculated from as few as two heartbeats, accurately estimating PNS activation from HRV data requires that HRV is assessed over multiple respiratory cycles, and conventional approaches typically rely on at

least 30 seconds of heartbeat data (Malik, 1996). More recently, a method for using spectral analysis for estimating HRV values at the second-by-second level has been developed (Gates, Gatzke-Kopp, Sandsten, & Blandon, 2015; Martínez et al., 2017). These approaches rely on a weighted moving-window approach, such that they arrive at estimates of HRV that weight data from a given second more heavily, but still utilizes 30 seconds of heart period data. This dissertation will take advantage of this approach, allowing for the types of change in HRV that are examined in within-person models and measures of HRV range to be examined at a temporal resolution that is closer to the time-scale of PNS change than traditional 30s estimates.

Within-person studies

While between-person studies have dominated research on PNS regulation, studies that use within-person approaches are increasingly common. Existing evidence suggests that PNS regulation in a cognitive challenge context can be captured by modeling intra-individual variability in HRV. Muth and colleagues (2012) used a multilevel modeling approach to examine within-person associations between subjective ratings of cognitive workload and HRV reactivity across seven cognitive challenge tasks. This study found a significant negative relationship between HRV reactivity and subjective rating of workload, suggesting that larger decreases in HRV relative to an individual's baseline HRV occurred when individuals were experiencing higher levels of cognitive demand. While this finding supports the idea that HRV fluctuates in response to changing task demands, no performance measures were reported in this study.

To date, only one study has directly measured the within-person relationship between intra-individual variability in HRV and intra-individual variability in task cognitive performance. Giuliano and colleagues (2017) examined the association of HRV reactivity and task performance across individual trials of a working memory task. A significant, positive

within-person association was found between HRV reactivity and task performance. The authors pointed out that this positive association differed from many of the findings from between-person studies, which have more often found that negative HRV reactivity was associated with improved task performance. They suggested that this difference may be due to the nature of the task that was used, which unlike many cognitive challenge tasks did not involve any time pressure as participants were given as much time as needed to complete trials. This interpretation is consistent with the idea that higher levels of PNS activation may facilitate task performance in contexts where participants are given time to engage in deliberation prior to responding to trials, owing to concurrent levels of elevated prefrontal activation (Thayer & Lane, 2009). However, this finding comes with several important caveats. First, the association between HRV reactivity and task performance was only found among individuals with low levels of baseline sympathetic activity (as measured by pre-ejection-period). Second, this study used a sample that was selected for high levels of exposure to early life stress, a factor that may impact the development of PNS regulation (Glackin, Hatch, Drury, & Gray, 2020).

Between vs Within-person Studies. In addition to providing novel information regarding within-person associations between PNS and cognitive regulation, within-person studies of HRV and task performance would allow for findings from between vs. within-person studies to be compared. There is evidence suggesting that psychophysiological relationships manifest differently at the within-person level. One study examined the association between blood pressure and self-reported anger during a memory recall procedure. While no between-person association was found between anger and blood pressure, a significant positive within-person association was reported (Zawadzki, Smyth, Sliwinski, Ruiz, & Gerin, 2017). Another study examining longitudinal relationships between measures of blood pressure and performance on several cognitive tasks found that there were

significant associations at both the between and within-person level, but that that the nature of these relationships differed (Thorvaldsson et al., 2012). These findings suggest that within and between-person associations between PNS regulation and cognitive regulation may differ in terms of whether a significant association is found, or instead predict unique associations. This dissertation will address these questions by assessing the relationship between HRV and task performance at both the between and within-person level.

Measuring net intra-individual HRV variability at the between-person level

The within-person models will be used to examine how intra-individual variability in HRV corresponds to intra-individual variability in task performance, with the goal of assessing the relationship between the processes of PNS and cognitive regulation. HRV range, which refers to the differences between an individual's maximum and minimum observed HRV values over a given period of time, will be used as a measure of net intra-individual variability, which quantifies intra-individual variability at the between-person level (Ram & Gerstorf, 2009). Measures of HRV range may reflect an individual's capacity to engage in PNS regulation, with larger within-person ranges reflecting PNS activity that is more responsive to environmental conditions. This is similar to the conceptual approach that some authors have taken toward baseline HRV, as higher baseline HRV is often treated as a marker of greater capacity for engaging in PNS regulation (Porges, 2007). This conceptualization of baseline HRV as a measure of regulatory capacity fits within a resource model framework that views PNS activity as a resource that is "spent" to meet task demands via PNS withdrawal (Baumeister, Muraven, & Tice, 2000). However, as a static measure, baseline HRV provides no direct information about changes in PNS activity over time. Because HRV range utilizes data from an individual's variability in HRV over time, it may serve as a more direct estimate of the capacity for PNS regulation compared to a static baseline measure.

HRV range during a cognitive challenge task. HRV range is similar to measures of HRV reactivity insofar as both quantify within-person change in HRV, although reactivity measures capture a single instance of change, while measures of net intra-individual variability summarize information about patterns of change over times. For example, fluctuations in HRV are known to occur within as well as between task conditions (Gatzke-Kopp & Ram, 2018), but this information is lost when a single on-task measure of HRV is computed and used to calculate a reactivity score. By quantifying the difference between an individual's maximum and minimum observed HRV value during performance of a cognitive challenge a task, HRV range may an estimate of the degree of PNS regulation that an individual engaged in. To date, no studies have examined the association between HRV range over the course of a task and measures of task performance. The nature of such an association would be informative, given that competing hypotheses may be presented on conceptual grounds. HRV range during a cognitive challenge task may be taken as an indicator of the extent to which an individual engaged in PNS regulation. On the one hand, more PNS regulation may indicate that an individual is successfully engaging with the task, thus predicting a positive relationship between HRV range and performance measures. On the other hand, more PNS regulation might indicate that an individual is struggling more with task demands, which would instead predict a negative relationship between HRV range and performance measures.

The use of HRV range as a measure of PNS regulation would represent a unique approach for examining the relationship between PNS and cognitive regulation, given that HRV range during a task provides no information about how high or low HRV values were. Both the between and within-person models described above are meant to determine whether lower or higher HRV values are associated with better task performance. Associations between HRV range and task performance would instead test whether greater or lesser

magnitudes of change in PNS activation predict task performance, irrespective of how high or low HRV values may be. Assessing net intra-individual variability may provide useful estimates of physiological regulation, given that healthy biological systems are typically characterized by a high degree of variability in activity levels, while a lack of variability is often an indicator of pathology (Cacioppo & Tassinary, 1990). Evidence that greater intra-individual variability in HRV may be marker of PNS regulation has been provided from two studies which used the standard deviations of HRV values during performance of a cognitive challenge task as between-person measures of intra-individual variability (Spangler, Gamble, McGinley, Thayer, & Brooks, 2018; Spangler & McGinley, 2020). They found greater intra-individual variability of HRV was related to more stability in performance levels across task conditions (in other words, less intra-individual variability in performance). This may indicate that variability in PNS activity functioned as a 'stability maintenance' process. However, these studies also examined the relationship between HRV range and task performance and found that they were unrelated.

HRV range across multiple tasks and contexts. In addition to measuring HRV range over the course of a single task, person-specific ranges could be measured over longer periods of time in which individuals engage in a range of tasks that have differential impacts on PNS activation. As discussed above, many cognitive challenge tasks have been found to lead to decreases in HRV relative to baseline levels. Other studies have found that HRV tends to be elevated during positive and decreased during negative social interactions (Shahrestani, Stewart, Quintana, Hickie, & Guastella, 2015). An individual's range of HRV across multiple tasks that elicit both decreases and increases in PNS activity would represent of an approximation of that individuals full range activity across different regulatory contexts. For the example, the data depicted in Figure 2 capture HRV during a variety of tasks that differ in terms of cognitive demand as well as social context. The use of multiple tasks should also

help to ensure that all individuals in a sample experience some contexts that elicit high and low levels of HRV, given that even tasks that pull for a specific pattern of change at the sample level typically elicit a combination of positive and negative HRV reactivity when individual response patterns are examined (Bush, Alkon, Obradovíc, Stamperdahl, & Boyce, 2011). The extent of between-person differences in within-person HRV range for the current sample is depicted in the top panel of Figure 3, which depicts the minimum and maximum HRV values observed for each participant over the course the experimental tasks used in the current study.

Hypothesized Relationships Between HRV Range and Task Performance. The current dissertation will analyze HRV range measured during task performance (HRV task-range) as well across several tasks over the course of a three-hour lab visit (HRV visit-range) to quantify the relationship between HRV range and task performance. Given the novelty of HRV range as measure of PNS regulation, the relationship between HRV range and task performance will be analyzed in an exploratory fashion. As mentioned above, HRV task-range may be positively or negatively related to task performance, depending on whether larger ranges indicate more successful utilization of the PNS to engage with task demands or a greater need for PNS regulation due to higher levels of subjective difficulty. Or, in line with previous studies of intra-individual variability in HRV (Spangler & McGinley, 2020), HRV task-range may be unrelated to performance measures. One reason that HRV task-range may be unrelated to task performance is that PNS regulation involves changes in physiology in response to changes in environmental demands. Thus, changes in HRV during the relatively stable demands of a single task may be less related to cognitive regulation than changes in HRV across task conditions. HRV range across a variety of task conditions may provide a better estimate of regulatory capacity, in which case HRV visit-range would be expected to have a positive relationship with cognitive regulation as measured by task performance.

Referring back to Neurovisceral heuristic model depicted in Figure 1, larger within-person HRV ranges across the lab visit may indicate a greater capacity to shift PNS activity along the x-axis, in order to match psychophysiological state to environmental demands that are fluctuating over time. And unlike measures of HRV taken concurrently with task performance, the relationship between HRV visit-range and task performance would not be expected to differ based on task type.

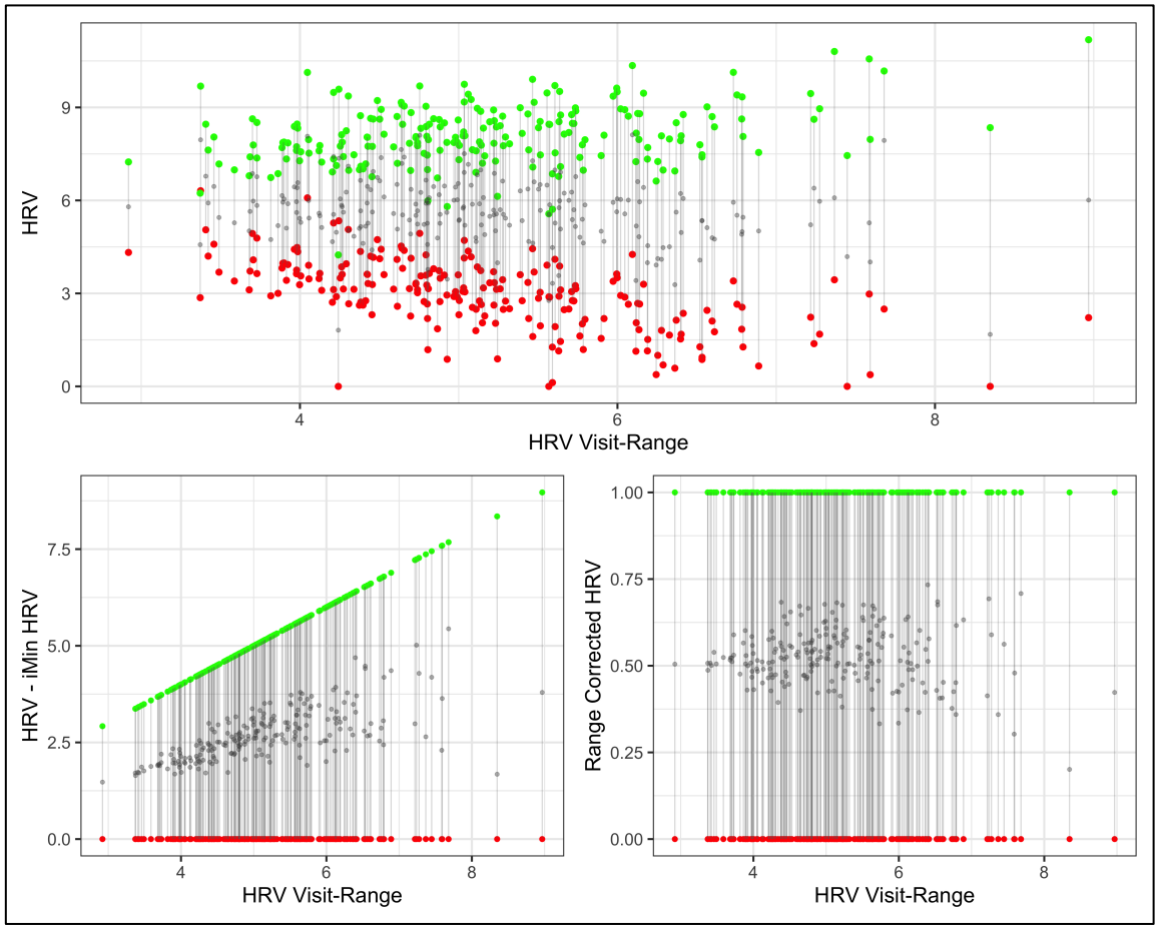

Figure 3. Depiction of within-person HRV range values derived from second-by-second estimates of HRV measured across each task of the lab visit for the current study. The top panel shows each individual's minimum (red dots) and maximum (green dots) observed HRV value. The vertical grey line connecting the two points represent within-person range, with individuals arranged from lowest to highest within-person HRV range. Grey dots represent the mean of all HRV values for each individual. The bottom two panels depict the two-step process of range correction applied to these HRV data. In the first step (bottom-left panel), individual minimum HRV values are subtracted. This results in all individuals having the same minimum value of 0, with each person's maximum value now representing their within-person range in raw values. In step two, these values are divided by within-person range to arrive at a range of 0-1 for every individual (bottom right panel).

There is an alternative interpretation of between-person differences in within-person range regarding physiological measures. Rather than reflecting meaningful between-person differences in the capacity for physiological regulation, it has been suggested that individual differences in within-person range may represent a source or measurement error for physiological variables, and thus between-person differences in range should be corrected for rather than used as an explanatory variable (Lykken, Rose, Luther, & Malley, 1966; Lykken, 1972). Curiously, while several recently published studies have corrected for between-person differences in within-person HRV range (Pattyn, Neyt, Henderickx, & Soetens, 2007; Lampinen et al., 2018), to date there has been no investigation as to whether HRV range is an important measure of PNS regulation or a nuisance variable that should be corrected for. A significant relationship between HRV range and task performance measures would support the former interpretation of HRV range. However, finding that HRV range is unrelated to task performance would be consistent with but not sufficient to establish that correcting for between-person differences in within-person HRV range is appropriate. This dissertation will take advantage of the available data of HRV range across a range of tasks, in order to assess both of these possible interpretations of HRV range. If evidence is found that larger HRV range predicts better cognitive regulation, then HRV range would provide an alternative to the between and within-person HRV measures described above. If instead HRV range appears to be something that should be corrected for, it would suggest that the existing between and within-person approaches to studying the relationship PNS and cognitive regulation may be improved using range correction. Methods for determining the appropriateness of range correction for HRV data are described below.

Conceptual and Methodological Considerations Regarding HRV Range Correction

HRV is well-validated measure of PNS activity (Cacioppo, 1994; Porges, 2007; Thayer, Ahs, Fredrikson, Sollers III, Wager, 2012). However, it cannot be assumed that two

individuals who have equivalent levels of HRV are experiencing equivalent *psychophysiological* states, given that purely physiological processes such as digestion, immune system regulation, and many others may contribute to between person differences in HRV independently of any psychological processes. For example, studies have found that mean levels of HRV differ based on factors that are known to contribute to differences in physiology such as sex, age, and body-mass index (BMI; Antelmi, De Paula, Shinzato, Peres, Mansur, & Grupi, 2004; Beauchaine, Bell, Knapton, McDonough-Caplan, & Zisner, 2019). This complicates the interpretation of between-person differences in HRV level in terms of what they suggest about between-person differences in psychophysiological sate. As an illustrative example, consider the finding that women tend have higher HRV on average compared to men (Antelmi et al., 2004). Within the framework of the Neurovisceral heuristic model depicted in Figure 1, one interpretation of this sex difference is that, on average, women are further to the right side of the x-axis and men and further to the left in terms of their level of PNS activation, which would correspond to prototypical differences in brain activity and cognitive state as well. This interpretation is certainly defensible, as many psychophysiological associations are characterized by significant sex differences (Nugent, Bain, Thayer, Sollers, & Drevets, 2011; Tracy & Giummara, 2017).

An alternative interpretation is that the mapping between manifest measures of HRV and the construct of PNS activation represented by the x-axis of Figure 1 differs between men and women. In other words, the same HRV value may represent different locations along the x-axis for the prototypical man vs. the prototypical woman. This thinking may be extended to individual differences, meaning that the mapping between HRV values and PNS activity may occur in a person-specific way. Stated differently, rather than representing PNS activity at the between-person level, the x-axis of Figure 1 can be thought of as representing PNS activity at the within-person level, such that where an individual falls along this axis at any given time is

determined by where they are within their person-specific state-space of PNS activity. In situations where the mapping between manifest and latent variables differs between individuals, a transformation of manifest variables may be appropriate (Nesselroade, Gerstorf, Hardy, & Ram, 2007). Range-correction represents one such transformation that may be appropriate for HRV data.

Range-correction is a simple transformation that involves two steps. The first step is to subtract each individual's minimum observed HRV value from all of their HRV measures. The final step is to divide each individual's HRV values by their person-specific HRV range, values that represent HRV as a proportion of within-person range. The effect of these steps on "raw" measures of HRV range are depicted in the bottom two panels of Figure 3. This approach views differences in within-person range as a source of measurement error for physiological variables (Lykken, Rose, Luther, & Maley, 1966; Roberts, 1979; Bush, Hess, and Wolfard, 1993). Lykken and colleagues (1966) performed a range-correction procedure on measures of skin conductance level, and compared the associations of "raw" and range-corrected skin conductance values with measures of reaction time. The use of range corrected values was associated with lower estimated standard errors, and a subsequently stronger correlation between skin conductance and task performance measures. If range-correction has a similar effect on the estimated relationship between HRV measures and task performance, it would suggest that range corrected HRV (RC-HRV) values may be a more accurate estimate of PNS activity compared to traditional raw values. Range-correction has been used in several studies that use HRV to assess PNS activity (Pattyn et al., 2007; Lampinen et al., 2018), although the authors of these studies did not provide a rationale for the use of range-correction. Interestingly, one study that measured both skin conductance and HRV used range-correction, but only for the skin conductance measures (Wendt, Neubert, Koenig,

Thayer, & Hamm, 2015). It is not clear why this procedure was considered necessary for skin conductance measures but not for HRV.

Range Corrected HRV in between and within-person studies

The potential effect of using RC-HRV rather than HRV on between-person analyses is explored in Figure 4, which compares baseline, on-task, and reactivity values for three individuals with different HRV ranges. The top panel of this figure expresses HRV using traditional raw HRV values. The vertical lines represent each individuals within-person HRV range, with the smallest HRV range on the left side and the largest on the right side. Two data points are represented for each individual, with the points on the left and right side of the vertical lines representing a baseline and on-task measure of HRV, and the slope connecting them representing a measure of HRV reactivity. In terms of between-person differences, the (blue) individual on the left side of the panel has the highest baseline HRV, while the second and third individual have successively lower baseline values. The individuals on the left and right side of the figure as have identical HRV reactivity values (+2), while the middle individual's reactivity value is twice as large (+4). And finally, the left and middle individual have identical on-task HRV values (9), while the third individuals on-task HRV is 5. The bottom panel of this figure shows the same data after range-correction was applied. The individuals on the left and right side of the figure as have identical Baseline HRV values, while the first second individual now have identical HRV reactivity values. These hypothetical data illustrate the potential of range correction to impact between person measures of HRV, and thus influence the findings of between-person analyses.

The use of RC-HRV values also would provide an alternative method for quantifying intraindiviudal variability in HRV over time. Currently, within-person studies of PNS regulation either rely on HRV reactivity (Giuliano et al., 2017) or mean-centered HRV values (Gatzke-Kopp et al., 2018) to model changes in HRV over the course of a task. The use of

RC-HRV to model PNS regulation as the within-person level would provide estimates of how where an individual's level of PNS activity at a given time falls within their "state-space" of PNS activation, rather than with respect to a single estimate of HRV like a baseline or mean value. As an illustration of how these measures may provide different information, consider the top panel of Figure 3. The gray dots depicting mean HRV values for each individual do not necessarily fall near the center of each individuals within-person range.

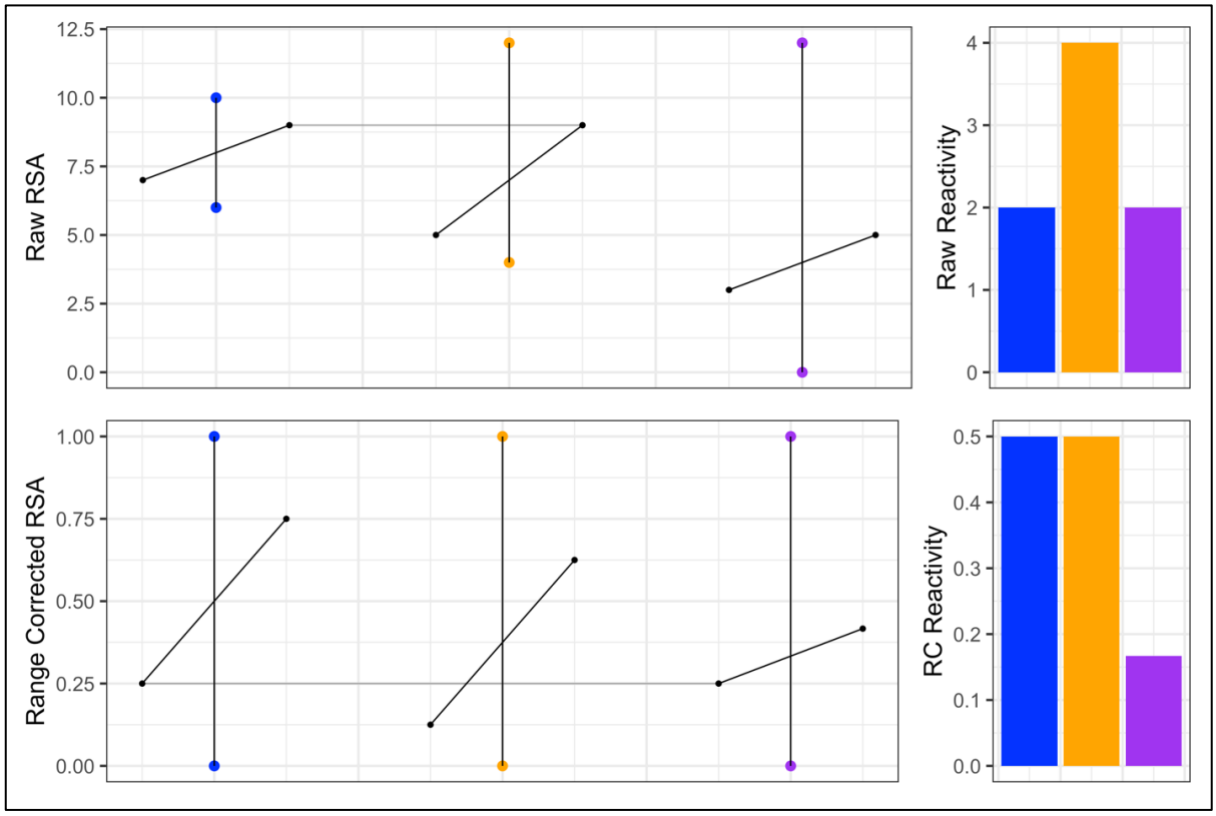

Figure 4. Hypothetical between-person HRV data for three individuals. Top-left panel shows raw HRV data. Vertical black lines represent individual ranges from minimum to maximum observed HRV values. Horizontal lines show within-person change from a baseline condition (left of the vertical line) to an on-task condition (right of the vertical line). All individuals differ in their baseline values. The first and second individuals have the same on-task HRV value of 9, as indicated by the gray line connecting them. Bottom-left panel shows range corrected HRV data, where between-person differences in within-person range have been removed. Using range-corrected values, the first and third individual have the same baseline value of 25 and each individual has a different on-task value. The top-right and bottom-right panels contain histograms showing between-person differences in within-person change for raw and range-corrected HRV. Using raw HRV values, the first and third individual show the same magnitude of reactivity (+2), while the second individual shows twice as much change (+4). When using range-corrected HRV to calculate reactivity, the first and second individuals show the same magnitude of reactivity (+50).

Research Questions and Hypotheses

This dissertation will seek to address four broad questions regarding the relationship between PNS regulation and cognitive regulation:1. Are between-person differences in HRV related to between-person difference in task performance? 2. Is intra-individual variability in HRV related to intra-individual variability in task performance? 3. Are between-person differences in within-person HRV range related to between-person difference in task performance?; and 4. What effect does the use of RC-HRV values have on findings regarding between and within-person associations between HRV and task performance?

In addition to each of these broad questions, more specific hypotheses regarding the ways that PNS and cognitive regulation are operationalized relate to findings will be tested. In terms of research question 1, the following hypothesis regarding the choice of HRV measures and task type will be examined;

- Hypothesis 1a: The relationship between measures of HRV taken during task completion (HRV Reactivity and On-task HRV) and task performance will be moderated by task type, such that it is negative for the rapid-responding task and positive for the deliberative task
- Hypothesis 1b: The relationship between HRV reactivity and task performance will be moderated by Baseline HRV

Research question 2 is also concerned with how HRV relates to task performance but will examine this relationship at the within-person level. The following hypothesis regarding will be examined;

- Hypothesis 2a: HRV reactivity will be negatively associated with task performance on the rapid-responding task, but positively associated with performance on the deliberative task

- Hypothesis 2b: The relationship between HRV reactivity and task performance will be moderated by Baseline HRV for both tasks
- Hypothesis 2c: The strength of the estimated relationship between HRV and task performance will be stronger for the within-person models relative to the between-person models

Research question 3 is concerned with the relationship between net-intraindividual variability in HRV (HRV range) and task performance. Given the novelty of HRV range as a measure of PNS regulation, the following exploratory questions will be addressed;

- Question 3a: Are between-person differences in HRV task-range related to task performance?
- Question 3b: Are between-person differences in HRV visit-range related to task performance?
- Question 3c: Are between-person differences in HRV visit-range related to physiological factors, specifically age, sex, and BMI?

Finally, research question 4 is concerned with the effect of applying range-correction to HRV data on findings of how HRV measures relate to task performance. The following exploratory questions will be addressed;

- Question 4a: What is the magnitude of the effect of range-correction on between-person HRV measures, as indicated by the correlation between raw HRV and RC-HRV values?
- Question 4b: Do substantive findings of either the between or within-person models differ depending on whether raw or RC-HRV values are utilized?

Methods

Participants

Participants were recruited as part of a larger study of the development of self-regulation in early childhood. Recruitment occurred through a university database of families with children, flyers and posters distributed in communities around the university, and in-person recruitment at community events. Families with children between the ages of 30-60 months were recruited from a small city and its surrounding townships in a Mid-Atlantic state in the United States. A total of 158 families participated in the study. Two parents attended 100 of the lab sessions and provided data, and only one parent attended 58 of the visits, either because it was a single-parent household or because only one parent was available on the day of the study. This resulted in a total of 258 adults participating.

The lab visits ranged from 3 to 4 hours in length (shorter when only one parent participated) and involved five separate acquisition periods during which participants completed a variety of tasks while their cardiac physiology was recorded. Because two major goals of this study required data on HRV range across the entire set of experimental procedures, analyses were limited to individuals who had useable HRV data from each of the five acquisition periods, which resulted in a total *N* of 214. Demographics for this sample are presented in Table 1. Participants ranged in age from 23 to 54 years old, with 127 female and 87 male participants. Data on education was also collected and coded as either “No secondary degree”, “Secondary degree”, or “Post-secondary degree”. This Education variable was used in models predicting task Accuracy, in order to account for potential differences in either the capacity and/or motivation of individuals to engage with cognitive challenge tasks that may be reflected in levels of educational attainment.

Two factors contributed to a further reduction in the sample size for the analyses involving task performance. Participants completed two cognitive challenge tasks, a modified

Table 1

Sample Demographics

Variable		
Age		
	Mean (SD)	36 (5.31)
	Min - Max	23 - 54
Sex (N, %)		
	Female	127, 59.35%
	Male	87, 40.65%
Education (N, %)		
	No secondary degree	34, 15.88%
	Secondary degree	100, 46.72%
	Post-secondary degree	80, 37.83%

Note. Demographic data for $N = 214$ individuals

version of a standard CPT, known as the AX-CPT with distractors (Ophir, Nass, & Wagner, 2009; Morales, Gomez-Ariza, & Bajo, 2013) and a novel Anagrams task that was developed for this study. Data loss due to errors with the E-prime software used to present the cognitive challenge tasks resulted in 196 individuals having task performance data for the AX-CPT task and 214 having task performance data for the Anagrams task. In addition, individuals were excluded from the AX-CPT task if they had an overall accuracy score below 50%, in line with previous studies (Morales et al., 2013). This resulted in 3 more individuals being excluded, resulting in a final N of 196 for the AX-CPT analyses. Likewise, two individuals were excluded from the Anagrams analyses who did not correctly solve any of the anagrams, resulting in a final N of 212 for the Anagrams task. The decision to exclude these individuals was motivated both by the fact that the failure to correctly solve a single anagram may have indicated that they did not understand or were not motivated to do the task, as well as the fact that they had zero intra-individual variability in task performance and thus could not be included in the within-person models.

Procedures

The study took place at the Child Study Center facility on the campus of a large public university in a mid-Atlantic state. All aspects of the study were approved by the

University's Institutional Review Board (#00005112). Although the study involved children as well as parents, only the procedures for collecting adult behavioral and physiological data are described. Participants arrived at the lab between 8 am and 6 pm where they were greeted by trained research assistants (RAs). One RA then conducted the informed consent procedures, while the other oriented the child to the observation room.

After consent was obtained, RAs collected height and weight measurements of each family member and outfitted participants with a seven-lead electrode array for electrocardiogram (ECG) and cardiac impedance measurement. Two electrodes were also placed on the palm of participants' non-dominant hand in order to collect electrodermal activity data. However, neither the impedance nor electrodermal data are considered in this study. These electrodes were attached to wireless PDAs that parents wore on a belt clip, which transmitted the data to a computer in the neighboring room. All participants were asked to avoid touching the electrodes and to minimize use of their non-dominant hand but were otherwise able to move normally. Each parent completed five separate acquisition periods, in-between which physiological data collection was stopped. These five acquisition periods included one dyadic acquisition in which parents completed a series of tasks with their child, a period of filling out questionnaires, the AX-CPT task, a social-speech task, and the Anagrams task.

For two parent visits, mothers and fathers completed tasks in a different order. Mothers first completed the dyadic acquisition with their child, then the acquisitions containing the AX-CPT, social-speech, and anagram tasks. The fifth and final acquisition period for mothers was when they filled out a series of questionnaires. The order of acquisition periods was the same for mothers during single-parent visits. Fathers first completed the questionnaires acquisition, then the AX-CPT, social-speech, and anagram acquisitions, and lastly the dyadic acquisition. The two dyadic acquisition periods were

designed to involve tasks that were conceptually similar, but different enough that they remained novel for the child (who completed both dyadic acquisitions). The AX-CPT, social-speech, and anagram acquisitions were identical for each parent asides from the different order in which they were completed. The primary difference in terms of measurement between mothers and fathers was the initial resting baseline period. Mothers completed the resting baseline during the dyadic acquisition, whereas fathers completed it during the questionnaires acquisition. However, while physiological data from this initial resting baseline was included in the calculation of HRV range, baseline HRV and HRV reactivity data that was used in analyses were derived from pre-task baselines that did not differ between parents.

Cognitive Challenge Tasks. Participants completed two cognitive challenge tasks. The AX-CPT task was used to examine cognitive regulation in the context of a rapid-responding task, while the Anagrams task was used as a deliberative task. For the acquisition containing the AX-CPT, parents were brought into a room by an RA who seated them at a table with a laptop. The RA told the participants to press the space bar on the laptop to view a short movie and then left the room. Participants then viewed a one-minute video of a starfield as a pre-task baseline period. This video has been used in prior research to assess baseline physiology (Gatzke-Kopp et al., 2020), and was also used for the Anagrams pre-task baseline. Once the video had ended, the RA returned and reviewed a slideshow of the task instructions with the participant. Participants were told they would be viewing a series of letters presented one at a time, grouped into sets of five. The first and last letter of each set would be red, while the three intervening letters would be white. Two adjacent keys of the laptop keyboard had been labelled “Yes” and “No”. Participants were instructed to press the “No” key for each of the first four letters in each set. For the fifth letter, which I will refer to as the “probe”, participants were given a rule for determining which key to press. If the first letter, which I

will refer to as the “cue”, were an “A” and the probe was an “X”, they were instructed to press the “Yes” key. In all other cases, they were meant to respond to the probe by pressing the “No” key. The RA instructed participants to only respond using their dominant hand and observed them performing 10 practice trials to ensure participants understood the task prior to leaving the room. Participants then completed 50 consecutive trials after which the laptop displayed a screen instructing them to take a short break before proceeding to complete a final set of 50 trials by pressing the space key. For trials where the cue letter was an “A” the correct response was not knowable until the probe was shown. Because these trials placed the greatest demands on participants in terms of how rapidly they had to determine and respond with the appropriate behavioral responses, analyses of the AX-CPT data will be limited to cue-A trials. This left two trial types for this task, AX trials where the correct behavioral response was “Yes”, and AY where the correct behavioral response was “No”.

The anagrams task was completed on the same laptop as the AX-CPT task, but with the “Yes” and “No” labels removed from the keyboard. The same starfield video was used to acquire a 60 second pre-task baseline, after which the RA went over task instructions with participants and then left the room. Participants completed a total of 40 trials, during which they were shown a 5-letter anagram and given a total of 15 seconds to enter the correct solution and press the “Enter” key. Participants could enter multiple responses on a single trial, either until time ran out or the correct response was given. When a correct response was entered participants were shown a screen indicating they had successfully completed that trial and were asked to wait the remainder of the 15-second period before the next trial. This was done to ensure that all participants completed the same number of trials (40) across the same approximate length of time (10 minutes). Of the 40 anagrams, 34 were selected from a previous study that investigated the difficulty of anagrams using Rasch analysis, which relies on an item response theory framework to estimate difficulty based on how global

performance metrics related to the probability of correctly solving a given anagram (Adams, Stone, Vincent, & Muncer, 2011). Anagrams were selected from the bottom, middle, and top third of the difficulty distribution, and categorically labeled as “easy”, “medium”, or “hard”. The other six anagrams were intentionally designed to be unsolvable in order to ensure that all participants had both correct and incorrect trials. Trials were grouped into four blocks, each separated by a 30s rest period. The first block was composed of four easy anagrams. The next three blocks consisted of twelve anagrams each, and included a mix of easy, medium, hard, and unsolvable trials. The presentation order of the anagrams was the same across individuals. Data from each of the 36 solvable trials were used in analyses, while data from the 4 unsolvable trials were excluded.

Measures

Individuals provided information on their sex and age via self-report, and RAs took measurements of height and weight which were used to calculate BMI for each participant. These measures were used in the current study to test for an association between physiological factors and within-person HRV range. The measures of task performance and HRV used to model the relationship between PNS regulation and cognitive regulation are described below.

Task Performance Measures

Cognitive regulation was operationalized using measures of performance on the AX-CPT and Anagrams tasks. Given that cognitive regulation was defined as matching one’s cognitive state to meet their current situational demands, better performance on each task is considered evidence of more successful cognitive regulation.

Accuracy. Accuracy was coded as either 0 or 1 for every trial of each of the cognitive tasks, with a 1 indicating that participants had either pressed the correct key in response to the probe on the AX-CPT task, or entered the correct solution on the Anagrams task. At the

between-person level, each individual had an overall Accuracy score for each task. For the AX-CPT task, Accuracy was expressed as the percentage of all cue-A trials that were responded to correctly. For the Anagrams task, Accuracy was expressed as the percentage of solvable trials where the correct response was entered. At the within-person level, each participant had a vector of binary Accuracy values for each task that indicated accuracy or inaccuracy on each trial. For both tasks, higher Accuracy was treated as an indicator of better cognitive regulation at the between-person level. At the within-person level, it was assumed that individuals engaged in more successful cognitive regulation during accurate vs. inaccurate trials.

Reaction Time and Solution Latency. In addition to Accuracy, each task also had a temporal variable related to task performance. A depiction of data from a single AX-CPT trial and the resulting Reaction Time value is shown in Figure 7. For the AX-CPT task this variable was Reaction Time, expressed as the length of time (in milliseconds) between the probe letter being shown and the behavioral response being entered. Reaction Time on trials where no response was entered was coded as NA, and these trials were excluded from analysis. Between-person measures of AX-CPT Reaction Time were quantified as the average Reaction Time across all cue-A trials in which a behavioral response was registered.

For the Anagrams task, the length of time between the beginning of a trial and the correct solution being entered was recorded, which I will refer to as Solution Latency. While the Reaction Time and Solution Latency measures both refer to measures of time prior to a response being entered, they have been given different names to distinguish them conceptually. Reaction Time simply measures the length of time between seeing the AX-CPT probe and pressing wither the “Yes” or “No” key; Reaction Time was calculated for all trials in which a response was entered regardless of its Accuracy. Solution Latency specifically refers to the length of time between viewing an Anagram and entering the *correct* response

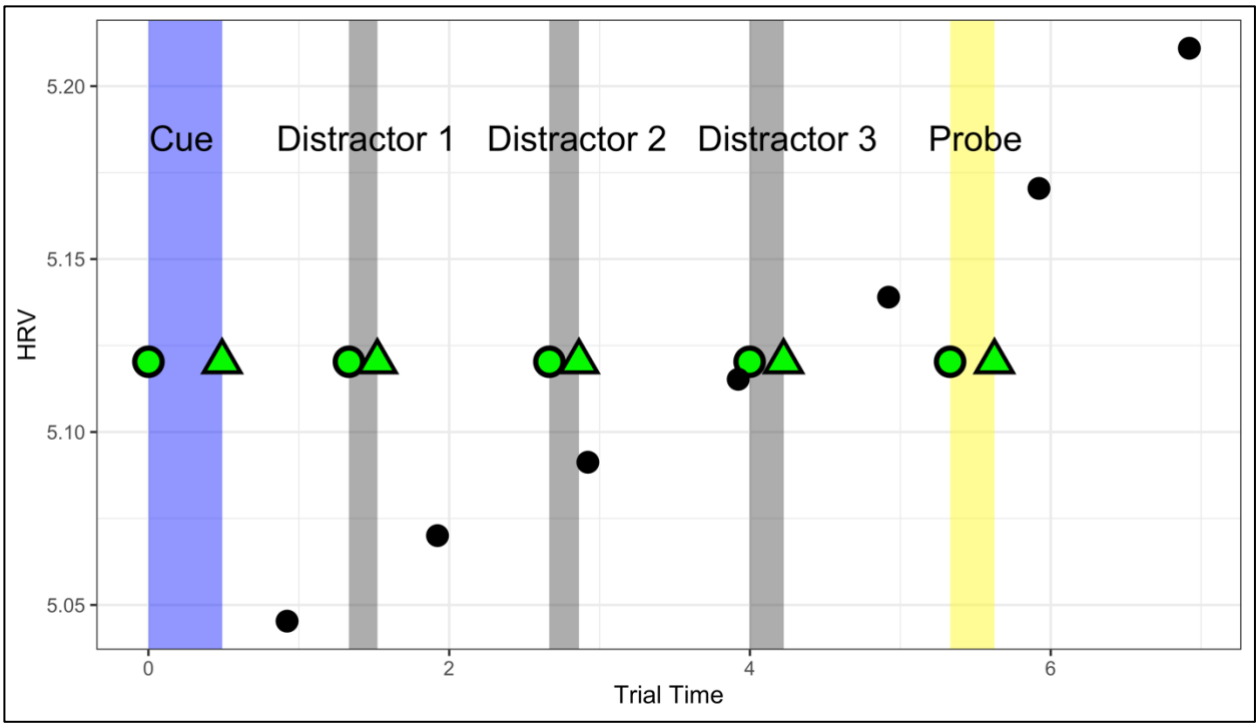

Figure 5: Data from a single trial of the AX-CPT task. The cue phase (blue rectangle), three distractors (grey rectangles), and probe phase (yellow rectangle) of the trial are shown, along with the timing of stimuli presentation (green circles) and behavioral responses (green *triangles).* The average of all HRV values (black circles) that occur prior to the behavioral response to the probe will be used to calculate trial-level HRV for this task.

(the timing of incorrect responses was not considered on the Anagrams task). Thus, while Reaction Time captures the speed of a *behavioral* response, Solution Latency is meant to capture the speed of the *cognitive* process that produces the correct solution. Between-person measures of Solution Latency were quantified as the average Solution Latency across all correct Anagram trials for each individual. Similar to Accuracy, Reaction Time and Solution Latency were represented as vectors of values for each individual. Lower Reaction Time and Solution Latency values were treated as indicators of better cognitive regulation at the between-person and within-person level.

HRV measures

During each task, cardiac physiology was monitored using a seven-lead electrode placement. Three electrodes were used to collect ECG data, one on each collar bone and a third place on the left hip. These were placed at the top and bottom of the sternum, and on the

spine, one inch above and below the top and bottom sternum electrodes. Data were sampled at 500 Hz using a wireless Mindware PDA and transmitted to a desktop computer running Biolab software (Version 3). Following data collection, ECG data were visually inspected and edited by trained RAs using Mindware HRV (Version 4.1) software. Briefly, the placement of R peaks was assessed for accuracy based on the ECG waveform. Erroneously placed peaks were deleted, and missing peaks were added when a clear waveform was present. If a single R peak was missing due to noise and no clear waveform was present, that peak was interpolated using the "midbeat" function. If noise prevented R peaks from being identified for more than one consecutive heartbeat, all misidentified peaks were deleted. Inter-beat intervals (IBIs) were measured as the length of time between successive R peaks, such that noisy segments where several consecutive peaks had been deleted led to unusually long IBIs. Cleaned ECG data containing a vector of IBI values for each individual/task was exported from Mindware into Excel. Any IBI values that were more than twice the length of each individual's average IBI were then recoded as missing.

Second-by-second HRV Estimation. A continuous estimate of HRV was computed using the rHRV package (Martínez et al., 2017), which applies spectral analysis in combination with a 30s moving Hanning-window technique to arrive at estimates of HRV centered on a single second of time. This technique incorporates information from the preceding and following 15 seconds of IBI data, weighting values that are closer to the focal point more strongly, producing an estimate of HRV for each second. This results in no data being available for the first and last 15 seconds of the measurement period, as there is insufficient information to estimate HRV. However, no data were lost for the periods of time (baselines + tasks) that were analyzed here, as the first and last 15 seconds of each measurement period did not contain any experimental tasks. Second by second estimates

were coded as missing if any IBI values within the 30s window had been identified as missing during ECG cleaning.

Baseline HRV. Baseline HRV measures for the AX-CPT and Anagrams tasks were calculated by taking the average of the second-by-second HRV measures that occurred during each of the two 60 second pre-task baseline periods. The sample distributions for baseline HRV for each of the cognitive challenge tasks are presented in the top row of Figure 6.

On-Task HRV. On-task HRV was calculated at the trial-level for each task, and a task-level value were then calculated by averaging across all relevant trial-level values. On-task HRV for the AX-CPT task was calculated as the average of all HRV values that occurred between the "cue" and "probe" phases of AX and AY trials (see Figure 7). On-task HRV for the Anagram task was computed as the average of HRV values that occurred during a trial, but prior to the anagram being solved. For example, for a trial where the correct solution is entered after 5.5 seconds, only the first 5 HRV values were used (see Figure 5). On trials that are never solved correctly, all HRV values were used. This is meant to ensure that the on-task HRV values for each person reflects their HRV while they are actively engaged in trying to solve an anagram. Sample distributions of on-task HRV for each task are depicted in the middle row of Figure 6.

HRV Reactivity. HRV reactivity was calculated at the task level as well as the trial level. Task-level HRV reactivity was calculated as average on-task HRV minus task-specific baseline HRV. Trial-level reactivity was calculated by subtracting each individual task-specific baseline HRV value from trial HRV values. Positive HRV reactivity values indicate that an individual's HRV was higher than their baseline level during that task/trial, while negative HRV reactivity values indicate that HRV was lower than during the baseline. Sample distributions of HRV reactivity for each task are depicted in the bottom row of Figure 6.

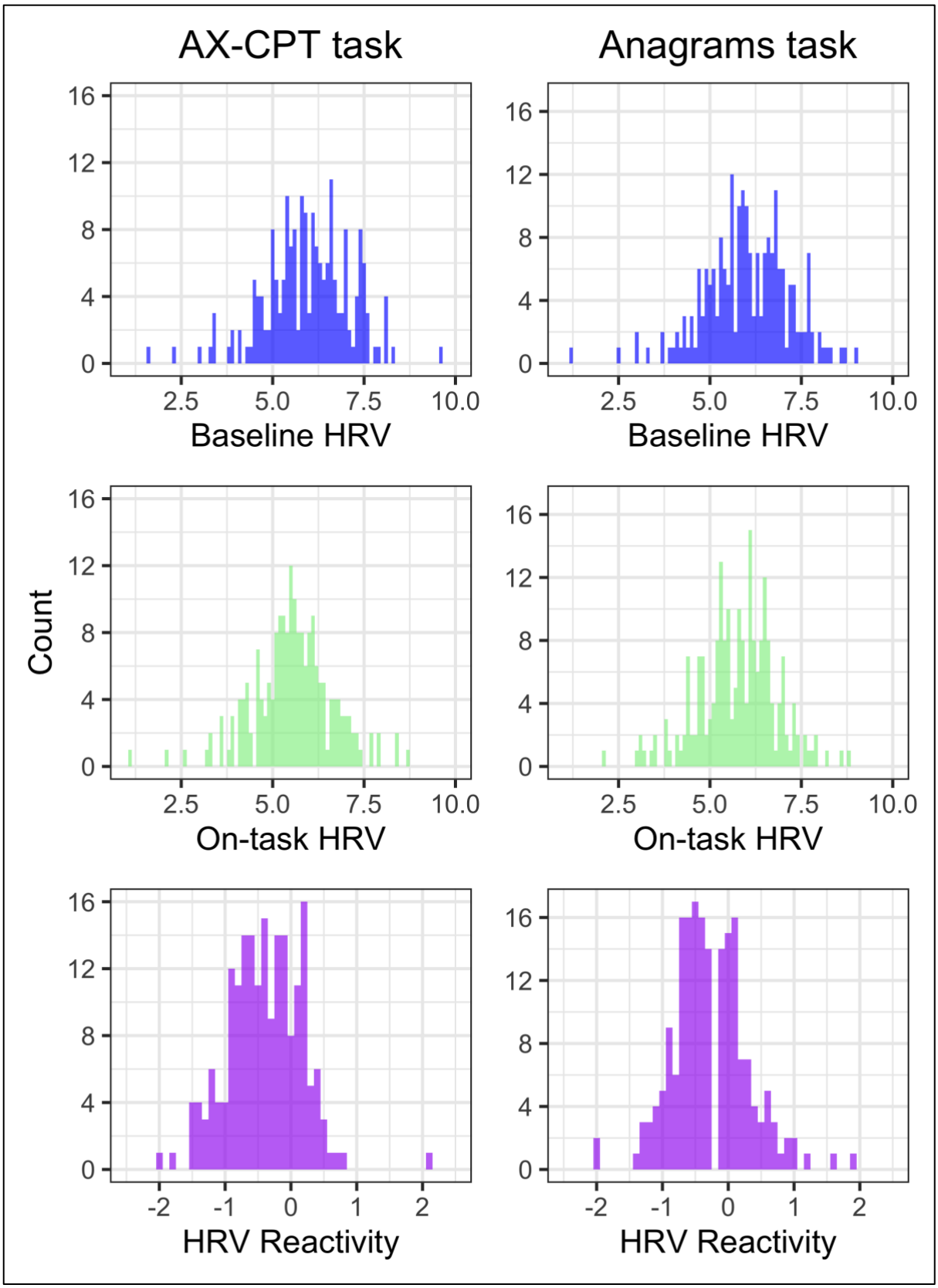

Figure 6: Distributions of between-person HRV measures for each task. Distributions for the AX-CPT and Anagrams task include data from $N = 196$ and $N = 212$ individuals respectively.

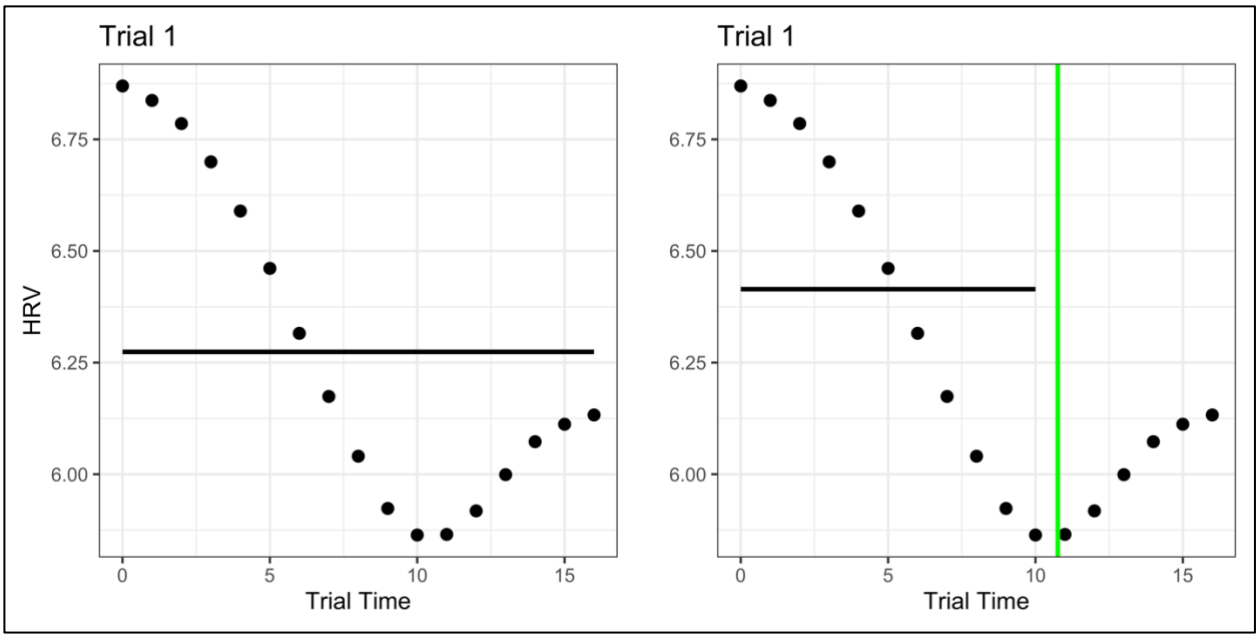

Figure 7. HRV data for one participant during a trial of the Anagram Task. Rather than taking the average of all HRV values during each trial (left), only values that occurred prior to solving an anagram will be used (right). The ability to selectively include or exclude data at the trial level is accommodated by the use of second-by-second HRV data. The average of all "pre-solution" HRV values across Anagram Task trials will be used as the "on-task" HRV variable for the Anagram Task.

Within-person HRV range. Within-person HRV range was calculated for each individual across each of the two cognitive challenge tasks (HRV task-range), as well as across all of the experimental portions of the lab visit (HRV visit-range).

Range-corrected HRV. Range-corrected versions of each between-person HRV variable (HRV, on-task HRV, and HRV reactivity) were obtained by subtracting an individual's minimum observed HRV value from that measure, and then dividing the result by their within-person HRV range. Resulting values were then multiplied by 100 so that they express HRV as a percentage of within-person range. This same procedure was applied to the within-person trial-level measures of HRV and HRV reactivity.

Analysis Plan

Analyses were conducted to address the four research questions laid out in the introduction; 1. Are between-person differences in HRV related to between-person difference in task performance? 2. Is intra-individual variability in HRV related to intra-individual

variability in task performance? 3. Are between-person differences in within-person HRV range related to between-person difference in task performance?; and 4. What effect does the use of RC-HRV values have on findings regarding between and within-person associations between HRV and task performance? The specific analyses that were conducted to address each of these questions are detailed below.

RQ1: Between-person associations of HRV and Task Performance

Two important aspects to this research question are whether the relationship between HRV and task performance depends on the specific HRV measure (baseline HRV, HRV reactivity, or on-task HRV) that is used, and whether the association differs between rapid responding and deliberative tasks. Based on prior evidence, a positive association between baseline HRV and task performance is predicted. However, associations between baseline HRV and task performance will not test the predictions of the heuristic model presented in Figure 1 of the introduction, as this model concerns *concurrent* associations between PNS regulation and cognitive regulation. In order to assess the validity of the Neurovisceral heuristic model, the two HRV measures that reflect PNS activity during task completion (HRV reactivity and on-task HRV) will also be assessed for a relationship with performance measures. It is hypothesized that HRV reactivity and/or on-task HRV will be negatively related to task performance on the AX-CPT task, such that larger reductions in HRV from baseline and/or lower HRV during that task are associated with higher Accuracy and faster Reaction Times. In contrast, it is hypothesized that the association between HRV and performance on the deliberative Anagrams tasks will be positive, as increases higher PNS activity should correspond with higher prefrontal activation which helps facilitate cognitive deliberation. Only the HRV variables are shown for these general equations, but Education was also entered as a covariate for the models predicting Accuracy. Likewise, Accuracy was entered as a covariate for the models predicting Reaction Time and Solution Latency.

Task Moderation. The hypothesis that task type will moderate the association between HRV and task performance was directly examined using an interactive model. Prior to this analysis, measure of task performance was scaled within each task so that data from both tasks may be analyzed in a single model. Specifically, each performance measure was scaled to have a mean of zero and a standard deviation of 1. The following equations were used to test for moderation of the relationship between HRV (both reactivity and on-task) and performance measures by task.

$$\text{Performance} = 1 + B_1\,(\text{Task}) + B_2\,(\text{Reactivity}) + B_3\,(\text{Task} * \text{Reactivity}) \;\xi \qquad \text{(EQ 1.1)}$$

$$\text{Performance} = 1 + B_1\,(\text{Task}) + B_2\,(\text{On-task}) + B_3\,(\text{Task} * \text{On-task}) \;\xi \qquad \text{(EQ 1.2)}$$

Baseline Moderation. While the above analyses were used to whether the relationship between concurrent measures of HRV and task performance differ between tasks, an additional set of analyses were used to assess whether baseline HRV moderated the association between HRV reactivity and performance within each task. Specifically, the following regression equations were used to predict each of the four task performance measures,

$$\text{Performance} = 1 + B_1\,(\text{Baseline}) + B_2\,(\text{Reactivity}) + \xi \qquad \text{(EQ 2.1)}$$

$$\text{Performance} = 1 + B_1\,(\text{Baseline}) + B_2\,(\text{Reactivity}) + B_3\,(\text{Baseline} * \text{Reactivity}) + \xi \qquad \text{(EQ 2.2)}$$

which used an additive and an interactive model to assess the combined relationship of baseline HRV and HRV reactivity to task performance.

RQ2: Within-person associations of HRV and Task Performance

The within-person association between trial-level HRV and trail-level performance was assessed using a multilevel model approach to accommodate the nested-structure of these data (Snijders & Bosker, 1999). This association was modelled in three models, one using HRV reactivity as the sole physiological predictor, a second controlling for between-person

differences in baseline HRV, and a third testing for an interaction between trial-level HRV reactivity and baseline HRV in predicting trial-level Task Performance. As with the between-person models, Education was entered as a control variable for the models predicting Accuracy, and Accuracy was entered as a control variable for the models predicting Reaction Time and Solution Latency. Trial-type was also entered as a time-varying predictor, in order to account for within-person variability in performance that is attributable to trial type rather than psychophysiological state. For the AX-CPT task, the two trial types are AX and AY trials. AX trials, which composed 80% of the trials, were used as the reference group. For the Anagrams task, the three trial types are Easy, Medium, and Hard trials (since Unsolvable trials were excluded from analysis) and Easy trials were used as the reference group.

Unlike the between-person Task Performance measures, Accuracy at the trial level must be modelled differently than Reaction Time and Solution Latency, since the former measure is binary while the latter two are continuous. Thus, for equations predicting trail-level Accuracy a generalized (logistic) linear multilevel model was utilized. The equation used to predict trial-level Accuracy has two levels. Level one has the following form;

$$Log(Accuracy)_{it} = \beta_{0i} + \beta_{1i}(Education_i) + \beta_{2it}(Trial\_Type_{it}) + \beta_{3it}(HRV\_Reactivity_{it}) + e_{it} \quad (3.1)$$

which models the log-likelihood that individual *i* successfully responds to trial *t* as a function of person-specific intercepts (β_{0i}) – corresponding to an individual's overall level of accuracy on a task – as well as their Education (β_{1i}), Trial Type (β_{2it}), HRV reactivity (β_{3it}). Unexplained variance is treated as residual error (e_{ti}) and assumed to be normally distributed. Level two includes two person-level variables; the random intercept for Accuracy (β_{0i}) and Education (β_{1i}). The equations for level two of this model are;

$$\beta_{0i} = \gamma_{00} + \gamma_{01i}(Accuracy_i) + u_{0i},$$

$$\beta_{1i} = \gamma_{10i} + \gamma_{11i}(Education_{SD}) + \gamma_{21i}(Education_{PSD})$$

where each individual's total level of Accuracy is modeled as a person-specific deviation (γ_{01i}) around the sample level average Accuracy (γ_{00}), and Education is represented as a categorical variable. This model represents the first of three that were run, with baseline HRV added at level two for a second model, and the cross-level interaction of baseline HRV and HRV reactivity added for the third model. The same set of three models were run to predict Reaction Time on the AX-CPT Task and Solution Latency on the Anagrams Task with two notable differences. First, a general linear multilevel model was used in place of a generalized linear model to accommodate the continuous nature of the outcome. Second, task-level Accuracy was used in place of Education as a person-level predictor.

Within-Person Hypotheses. Based on the predicted relationship between PNS activation and activity brain structures underlying cognition expressed in Neurovisceral Integration Theory (Thayer & Lane, 2000; Thayer & Lane, 2009) and depicted in Figure 1, I hypothesize that the relationship between trial-level HRV Reactivity and Task Performance will differ for the AX-CPT and Anagrams Task. For the AX-CPT Task, which requires rapid behavioral responding, I predict that more negative HRV reactivity will be predictive of better trial-level performance (higher log-odds of Accuracy and shorter Reaction Times). For the Anagrams Task, which requires deliberation, I predict that more positive HRV reactivity will be predictive of better trial-level performance (higher log-odds of Accuracy and lower Solution Latency). I further hypothesize that baseline HRV will not be predictive of trial-level performance at the within-person level, given that between-person differences in average performance are being accounted for using a random intercept. However, a significant between-person relationship between baseline HRV and Task Performance may manifest as a significant positive correlation between the fixed effects for baseline HRV and the random intercept.

RQ3: Relationship between HRV Range and Task Performance

Within-person HRV range during each of the two cognitive tasks will be quantified for each individual as a measure of net intra-individual variability and assessed for a relationship with Task Performance. This analysis is meant to explore a possible alternative to the Neurovisceral model in terms of how PNS activity relates to task performance. If HRV task-range is associated with task performance, it would suggest that PNS regulation may be better measured using metrics of intra-individual variability in HRV rather than measures of HRV level or reactivity. Within-person HRV range across all of the tasks (HRV visit-range) was also be quantified. The relationship between HRV visit-range and Task Performance measures was assessed, with the assumption that any significant association would indicate that between-person differences in within-person HRV range are a meaningful indicator of individual differences in psychophysiological regulation. The relationship between HRV visit-range and several physiological variables (age, sex, and BMI) were also assessed using multiple regression, to determine whether more purely physiological factors may explain between-person differences in within-person HRV range.

RQ4: Effects of Range Correction on HRV measures and their association with task performance.

Exploratory analyses were conducted comparing raw and RC-HRV values. Raw and RC-HRV values were correlated in order to determine the magnitude of the effect that range correction has on HRV values. The between and within-person models were then run using RC-HRV in place of raw HRV values. The goal of this analysis is to compare the findings obtained using RC HRV to the findings obtained from using raw HRV values. This goal will be achieved by first comparing the substantive findings between respective models, and noting any divergence between results when raw vs. range-corrected HRV values were used. As a follow-up analysis, in any case where substantive findings differ between models based

on the type of HRV values that were used, models were compared to see if they statistically differ in their goodness-of-fit using Cox analysis (Pearson, 1990).

Results

Between-Person Analyses

Descriptives

Descriptives for the four task performance measures can be found in Table 1. Average Accuracy on the AX-CPT task ranged from 64.77% to 100%, with a sample mean of 89.95%. There was more variability in Accuracy on the Anagrams task, with scores ranging from 2.5% to 77.5% and a sample mean of 44.54%. Average Reaction Time on the AX-CPT task was 354.74 ms, with a minimum of 232.24 ms and a maximum of 777.45 ms. Average Solution Latencies on the Anagrams Task ranged from 3.94 seconds up to 12.35 seconds and a mean of 7.41 seconds. The descriptives for baseline HRV, HRV reactivity, and on-task HRV measures can be found in Table 2, and the zero-order correlations between HRV and performance measures can be found in Table 3. The only significant correlation was between on-task HRV and solution latency on the Anagrams task (r = -0.15, p = 0.03).

Table 2

Performance Descriptives

Task	Variable	n	Mean (SD)	Min	Max
AX-CPT					
	Accuracy (%)	196	89.95 (6.30)	64.77	100.00
	Reaction Time (ms)	196	354.74 (74.49)	232.24	777.45
Anagrams					
	Accuracy (%)	212	44.54 (17.82)	2.50	77.50
	Solution Latency (s)	212	7.41 (1.53)	3.94	12.35

Note: For the AX-CPT task, all measures are specific to “Cue A” trials (AX and AY trial types). For the Anagrams Task, Accuracy refers to the percentage of solvable Anagram Trials that were correctly solved. Solution Latency refers to the average time (in seconds) that was taken to provide the answer to correctly solved anagrams.

Table 3

Descriptives table of between-person HRV measures across tasks

Task	Measure	Mean (SD)	Min	Max
AX-CPT				
	Baseline HRV	5.95 (1.16)	1.62	9.64
	HRV Reactivity	-0.40 (0.63)	-3.31	2.66
	On-Task HRV	5.56 (1.10)	1.11	8.73
Anagrams				
	Baseline HRV	6.0 (1.16)	1.16	8.97
	HRV Reactivity	-0.27 (0.56)	-2.03	1.93
	On-Task HRV	5.73 (1.12)	0.69	8.77

Table 4

Correlations between Performance and HRV measures on the AX-CPT and Anagrams Task

Task	Measure	Accuracy	RT/SL
AX-CPT			
	Baseline HRV	0.09	-0.03
	HRV Reactivity	0.07	0.12
	On-Task HRV	0.13	0.04
Anagrams			
	Baseline HRV	0.05	-0.10
	HRV Reactivity	0.01	-0.10
	On-Task HRV	0.06	-0.15*

Note: * = $p < 0.05$

Education was entered as a control variable for all models predicting Accuracy, with the “No secondary degree” group serving as the reference category. The decision to control for Education was based on the assumption that different levels of educational attainment

may correlate with differences in either the capacity or motivation to engage in cognitive regulation during these tasks. Accuracy was entered as a control variable for the models predicting Reaction Time (AX-CPT) and Solution Latency (Anagrams). Performance and HRV measures were scaled within-tasks to have a mean of 0 and standard deviation of 1 prior to analysis. This means that, for example, an Accuracy value of 0 corresponds to an average level of Accuracy on a given task. Between-person models were run testing whether the relationships between two of the HRV measures (HRV reactivity and on-task HRV) and performance measures were moderated by task type using EQ 1.1 and EQ 1.2.

Task Moderation Results

Results for the regressions predicting Accuracy and Reaction Time/Solution Latency using HRV reactivity are presented in Table 5. Task type did not moderate the association between HRV reactivity and Accuracy. However, a significant interaction was found between HRV reactivity and task type predicting Reaction Time/Solution Latency. This interaction was probed by plotting the estimated slope of HRV reactivity for each task. As shown in Figure 8, the pattern of this moderation was as predicted by the Neurovisceral heuristic model. Specifically, there was a negative association between HRV reactivity and Reaction Time for the AX-CPT task and a positive association for the Anagrams task. In other words, decreases in HRV from baseline was associated with faster Reaction Times on the rapid-response task while increases in HRV predicted shorter Solution Latencies on the deliberative task. However, a follow-up simple slopes analysis revealed that only the slope for the Anagrams task was significant ($B = 0.23$, $p = 0.04$) while the slope for the AX-CPT task was not ($B = -0.18$, $p = 0.14$). This same moderation analysis was repeated, using on-task HRV in place of HRV reactivity. Results of this analysis are presented in Table 6. The relationship between on-task HRV and Accuracy was not moderated by task type, but the relationship between on-task HRV and Reaction Time/Solution Latency was as shown in Figure 9.

Table 5

Moderation of the Association Between HRV Reactivity and Performance by Task

Outcome	Term	Estimate	p	Adjusted R2
Accuracy				
	Intercept	-0.366*	0.009	0.026
	Education: SD	0.444*	0.002	
	Education: Post-SD	0.570*	>0.001	
	HRV Reactivity	0.142	0.208	
	Task (Anagrams)	-0.056	0.620	
	Task * Reactivity	-0.133	0.424	
RT/SL				
	Intercept	0.090	0.270	0.075*
	Accuracy	-0.267*	>0.001	
	HRV Reactivity	-0.138	0.209	
	Task (Anagrams)	0.226*	0.039	
	Task * Reactivity	-0.401*	0.013	

Note: All continuous variables were scaled to have a mean of 0 and standard deviation of 1 prior to analysis. SD = secondary degree, HRV = heart rate variability. * = $p < 0.05$

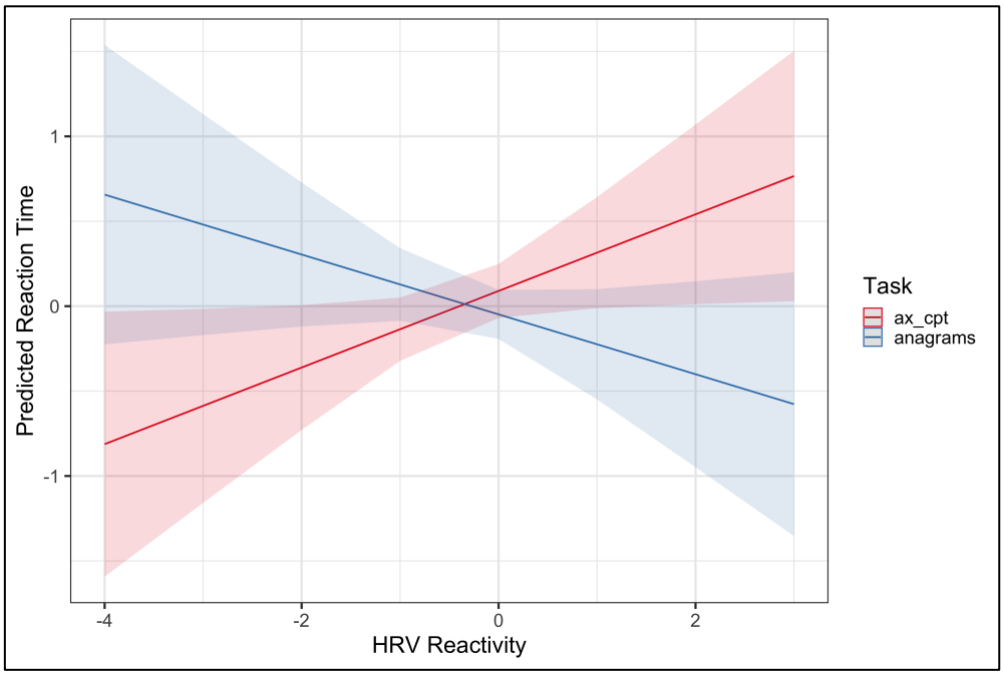

Figure 8. Depiction of the significant moderation of the association between HRV reactivity and Reaction Time/Solution Latency presented in Table 5.

Table 6

Moderation of the Association Between On-Task HRV and Performance by Task

Outcome	Term	Estimate	p	Adjusted R2
Accuracy				
	Intercept	-0.751	1.00	0.034
	Education: SD	0.426*	0.037	
	Education: Post-SD	0.575*	0.026	
	On-Task HRV	0.058	0.909	
	Task (Anagrams)	-0.373	0.470	
	Task * HRV	0.069	0.440	
RT/SL				
	Intercept	0.685	0.293	0.043
	Accuracy	-0.263*	>0.001	
	On-Task HRV	0.068	0.284	
	Task (Anagrams)	1.062*	0.033	
	Task * HRV	-0.187*	0.031	

Note: All continuous variables were scaled to have a mean of 0 and standard deviation of 1 prior to analysis. SD = secondary degree, HRV = heart rate variability. * = $p < 0.05$

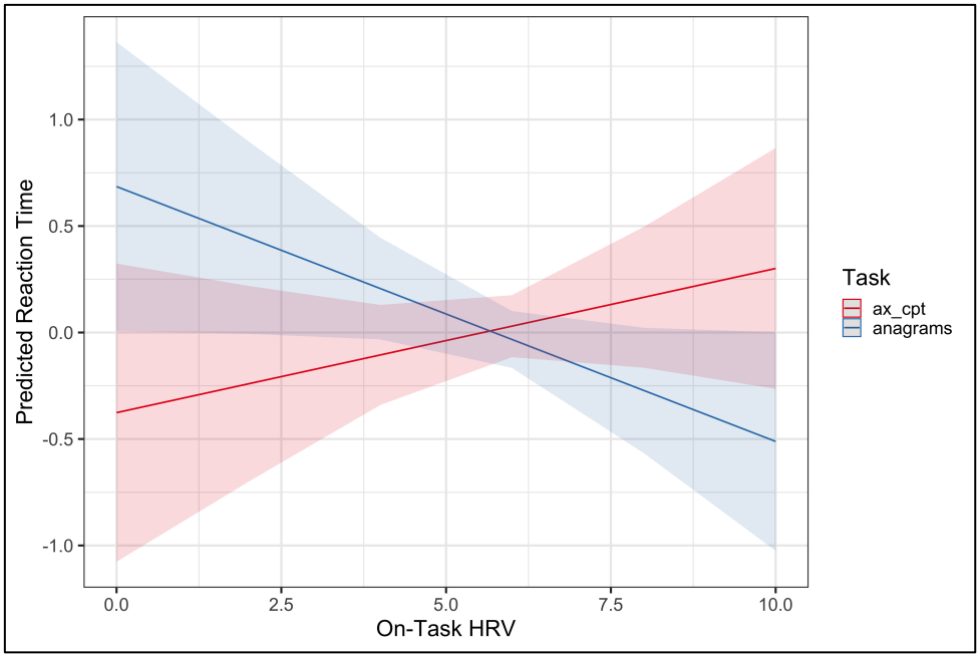

Figure 9. Depiction of the significant moderation of the association between on-task HRV and Reaction Time/Solution Latency presented in Table 6.

Baseline Moderation Results

Baseline HRV did not moderate the relationship between HRV reactivity and either of the AX-CPT performance measures, nor did it moderate the association between HRV reactivity and Accuracy on the Anagrams task. The interaction between baseline HRV and HRV reactivity was significant when predicting Solution Latency on the Anagrams task as seen in Table 7 (B = -0.098, p = 0.538). This interaction was probed by plotting the estimated slopes of HRV reactivity for individuals with average baseline HRV, or baseline HRV that

Table 7

Baseline HRV and HRV Reactivity predicting Anagrams Solution Latency

Equation	Term	Estimate	p	Adjusted R2
1				
	Intercept	>0.000	1.00	0.514
	Accuracy	-0.715*	>0.001	
	Baseline HRV	-0.059	0.223	
2				
	Intercept	-0.046	0.386	0.519
	Accuracy	-0.717*	0.001	
	HRV Reactivity	-0.094^{+}	0.051	
3				
	Baseline HRV	-0.098^{+}	0.052	0.526
	HRV Reactivity	-0.124*	0.014	
4				
	Baseline * Reactivity	-0.098*	0.011	0.538

Note. * = $p < 0.05$.

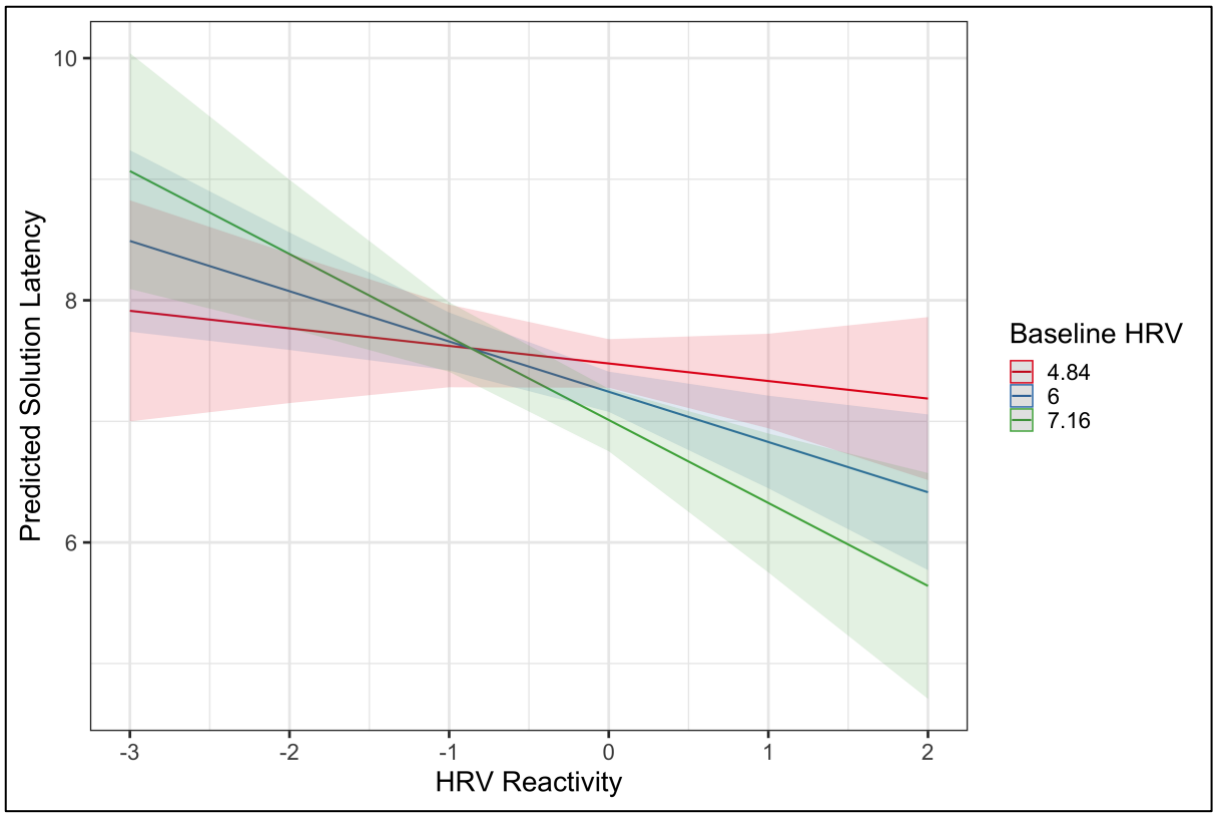

Figure 10. Visualization of the interaction between baseline HRV and HRV reactivity in predicting Solution Latency on the Anagrams Task modeled at the between-person level (see Table 7).

was one standard deviation above or below the mean (see Figure 10). This revealed the estimated negative relationship between HRV reactivity and Solution Latency was stronger among individuals with higher levels of baseline HRV.

Within Person

AX-CPT. Results from the multilevel model predicting trial-level Accuracy on the AX-CPT using baseline HRV (a person-level variable) and Trial HRV reactivity (trial-level variable) are shown in Table 8. As expected, AY trials were associated with significantly lower log-odds of trial Accuracy. In line with the hypothesis that lower levels of HRV during the AX-CPT Task should be associated with better performance, there was a significant negative association between Trial HRV reactivity and trial-level Accuracy (B = -0.125, p < 0.001), suggesting that decreases in HRV were associated with higher log-odds of Accuracy.

An additional model was run testing for a cross-level interaction between baseline HRV and Trial HRV reactivity which was not significant.

Results from the interaction model predicting trial-level Reaction Time on the AX-CPT task are shown in Table 9. A significant positive association between Trial HRV Reactivity and Reaction Time was found in a model with no interaction term (results not shown), indicating that more positive reactivity was associated with slower Reaction Times. This is in line with the hypothesis that *lower* HRV during task performance facilitates more rapid responding. There was also a significant cross-level interaction between baseline HRV and Trial HRV reactivity ($B = 0.016$, $p = 0.019$). The nature of this interaction was examined by plotting the estimated slopes of Trial HRV Reactivity for individuals with average baseline HRV, or baseline HRV that is one standard deviation above or below the mean (see Figure 11). This revealed that the estimated relationship between Trial HRV reactivity and trial-level Reaction Time was stronger (more positive) with increasing baseline HRV.

Table 8

Multilevel Logistic Model Predicting Trial-level Accuracy on the AX-CPT Task

Type	Terms	Estimate	95% CI
Fixed Effects			
	Intercept	2.139*	[1.841, 2.424]
	Education: SD	0.442*	[0.123, 0.802]
	Education: Post SD	0.396*	[0.044, 0.745]
	Trial Type (AY)	-1.063*	[-1.184, -0.942]
	Baseline HRV	0.081	[-0.041 – 0.202]
	Trial HRV Reactivity	-0.125*	[-0.190, -0.060]
Random Effects			
	Intercept	0.755	[0.186, 1.324]

Note: All continuous values were scaled to have a mean of 0 and sd of 1. * = $p < 0.05$

Table 9

Multilevel Model Predicting Trial-level RT on the AX-CPT Task

Type	Terms	Estimate	95% CI
Fixed Effects			
	Intercept	-0.068*	[-0.137, -0.001]
	Accuracy	0.113*	[0.046, 0.180]
	Trial Type (AY)	0.595*	[0.557, 0.632]
	Baseline HRV	-0.020	[-0.088, 0.048]
	Trial HRV Reactivity	0.028*	[0.011, 0.045]
	BL * Reactivity	0.016*	[0.002, 0.030]
Random Effect			
	Intercept	0.471	[0.250, 0.692]
	Residual	0.834	[0.139, 1.53]

Note: All continuous values were scaled to have a mean of 0 and sd of 1. * = $p < 0.05$

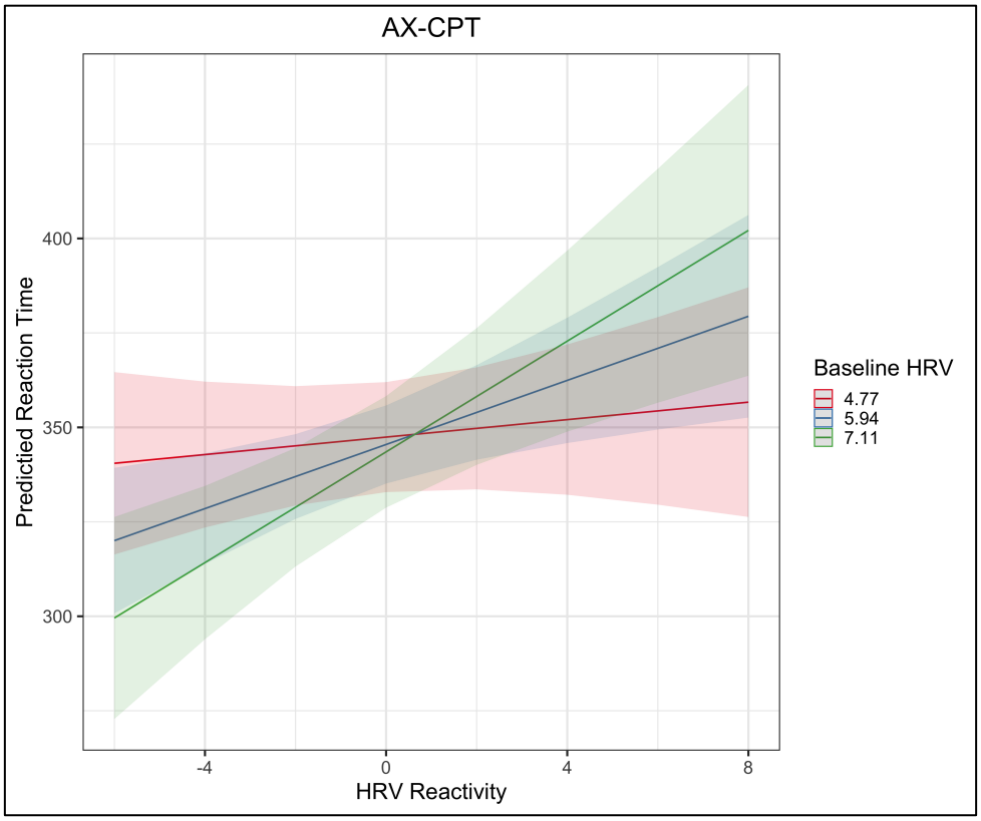

Figure 11. Examining the estimated slopes for the significant interaction between Baseline HRV and Trial HRV Reactivity predicting AX-CPT Reaction Time (see Table 9).

Anagrams

Results from the multilevel model predicting trial-level Accuracy on the Anagrams Task using baseline HRV and Trial HRV reactivity are shown in Table 10. As expected, Medium and Hard trial types were associated with increasingly lower odds of trial Accuracy. In line with the hypothesis that higher levels of HRV during the Anagrams Task should be associated with better performance, there was a significant positive association between Trial HRV reactivity and trial-level Accuracy (B =0.222, $p < 0.001$). An additional model was run testing for a cross-level interaction between baseline HRV and Trial HRV reactivity, but the interaction was non-significant.

Table 10

Multilevel Logistic Model Predicting Trial-level Accuracy on the Anagrams Task

Type	Terms	Estimate	95% CI
Fixed Effects			
	Intercept	0.402^{+}	[-0.048, 0.851]
	Education: SD	1.071*	[0.542, 1.604]
	Education: Post SD	0.686*	[0.173, 1.203]
	Trial Type (Medium)	-1.006*	[-1.132, -0.881]
	Trial Type (Hard)	-3.936*	[-4.181, -3.700]
	Baseline HRV	0.142	[-0.038, 0.323]
	Trial HRV Reactivity	0.222*	[0.147, 0.300]
Random Effects			
	Intercept	1.233	[1.100, 1.389]

Note: All continuous values were scaled to have a mean of 0 and standard deviation of 1. * = $p < 0.05$

A final within-person model was used to predict Solution Latency on the Anagrams Task. There was a significant negative association between Trial HRV reactivity and trial

level Solution Latency, suggesting that higher HRV reactivity during the Anagrams task was associated with better performance (solving anagrams faster). There was also a significant cross-level interaction suggesting that this association was moderated by baseline HRV (see Table 11). The nature of this interaction was examined by plotting the estimated slopes of Trial HRV reactivity for individuals with average baseline HRV, or baseline HRV that is one standard deviation above or below the mean (see Figure 13). This revealed that the estimated relationship between trial HRV reactivity and trial-level Reaction Time was stronger (more positive) with increasing baseline HRV. In keeping with the other two models that found a significant interaction term for baseline HRV and HRV reactivity, the predicted relationship between reactivity and performance was stronger for individuals with higher baseline HRV.

Table 11

Multilevel Logistic Model Predicting Trial-level SL on the Anagrams Task

Type	Terms	Estimate	95% CI
Fixed Effects			
	Intercept	>0.013	[-0.066, 0.040]
	Accuracy	-0.396*	[-0.437, -0.336]
	Trial Type (Medium)	0.286*	[0.227, 0.344]
	Trial Type (Hard)	1.074*	[0.907, 1.239]
	Baseline HRV	-0.072	[-0.118 , -0.267]
	Trial HRV Reactivity	-0.110*	[-0.144, -0.078]
	BL * Reactivity	-0.062*	[-0.090, -0.034]
Random Effect			
	Intercept	0.242	[0.202, 0.284]
	Residual	0.884	[0.863, 0.904]

Note: All continuous values were scaled to have a mean of 0 and sd of 1. * = $p < 0.05$

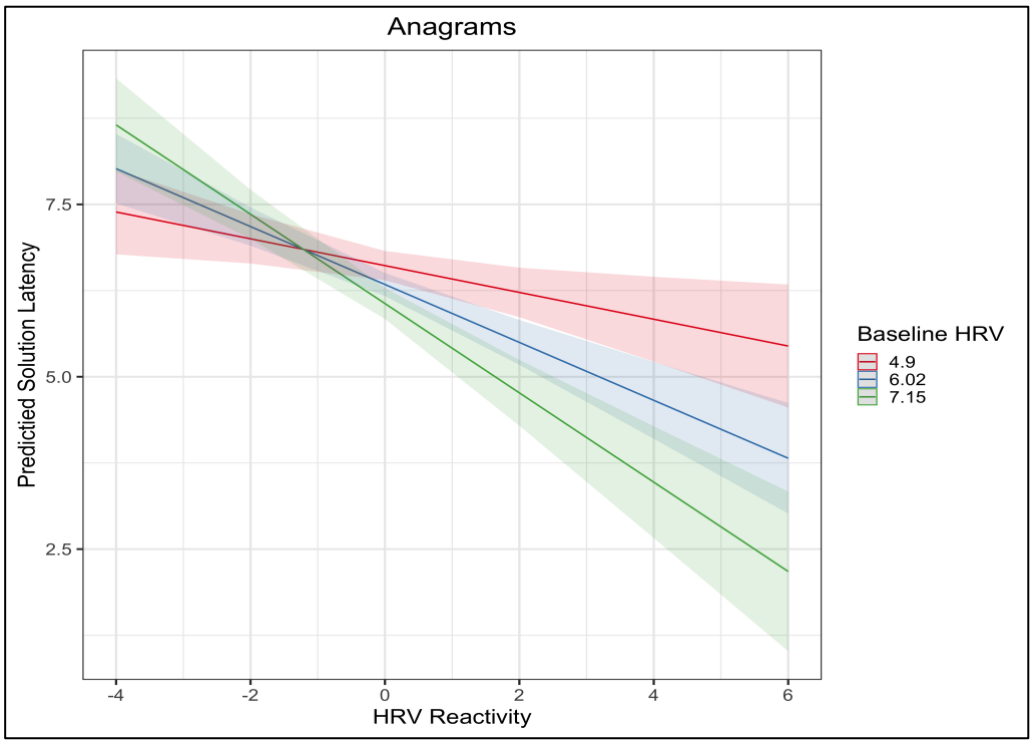

Figure 12. Moderation of the model predicted association between Trial HRV Reactivity and Solution Latency by Baseline HRV on the Anagrams task.

HRV Range

Within-person HRV-Ranges across each of the two challenge tasks, as well as across all of the experimental conditions of the lab visits, were calculated as estimates of net intra-individual variability across two different time scales. Descriptives for the two HRV task-range and the HRV visit-range variables are shown in Table 12. The columns in this table showing minimum and maximum values of within-person range values at the between-person level. For example, the individual with the lowest HRV task-range during the AX-CPT task had a range of 1.55.

Table 12

Descriptives for HRV Task Range and HRV Visit Range

Measure	Mean (SD)	Min	Max
CPT Range	2.96 (0.92)	1.55	8.29
AG Range	2.49 (0.74)	1.15	6.57
Visit Range	5.16 (1.01)	2.92	8.97

Task Range

Regressions were run using HRV task-range to predict each of the four task performance measures. In line with the previous between-person models, Education was controlled for in models predicting Accuracy, and Accuracy was controlled for in models predicting Reaction Time and Solution Latency. Estimated slopes for HRV Task Range across each task and performance measure can be seen in Table 13. None of the estimated slopes were significant, suggesting that HRV range during a task is not related to how well an individual performed.

Table 13

Relationship Between HRV Task-range and Performance Measures

Task	Outcome	Estimate	p
AX-CPT	Accuracy	-0.185	0.706
	RT	8.815	0.120
Anagrams	Accuracy	0.299	0.855
	SL	0.043	0.664

Note: RT = Reaciton Time, SL = Solution Latency. Models testing for a relationship between task-range and Accuracy controlled for Education, while models predicting RT and SL controlled for Accuracy (estimates for control variables not shown).

Visit Range

The association between HRV visit-range and task performance was assessed using the same models as were used for HRV task-range. HRV visit-range was not significantly associated with performance on the AX-CPT Task, or Accuracy on the Anagrams Task (see Table 14). However, there was a significant positive association between visit range and Solution Latency, indicating that individuals who had a larger range of HRV values over the course of the lab visit also tended to take longer to solve anagrams ($B = 0.198$, $p = 0.006$) (see Figure 13).

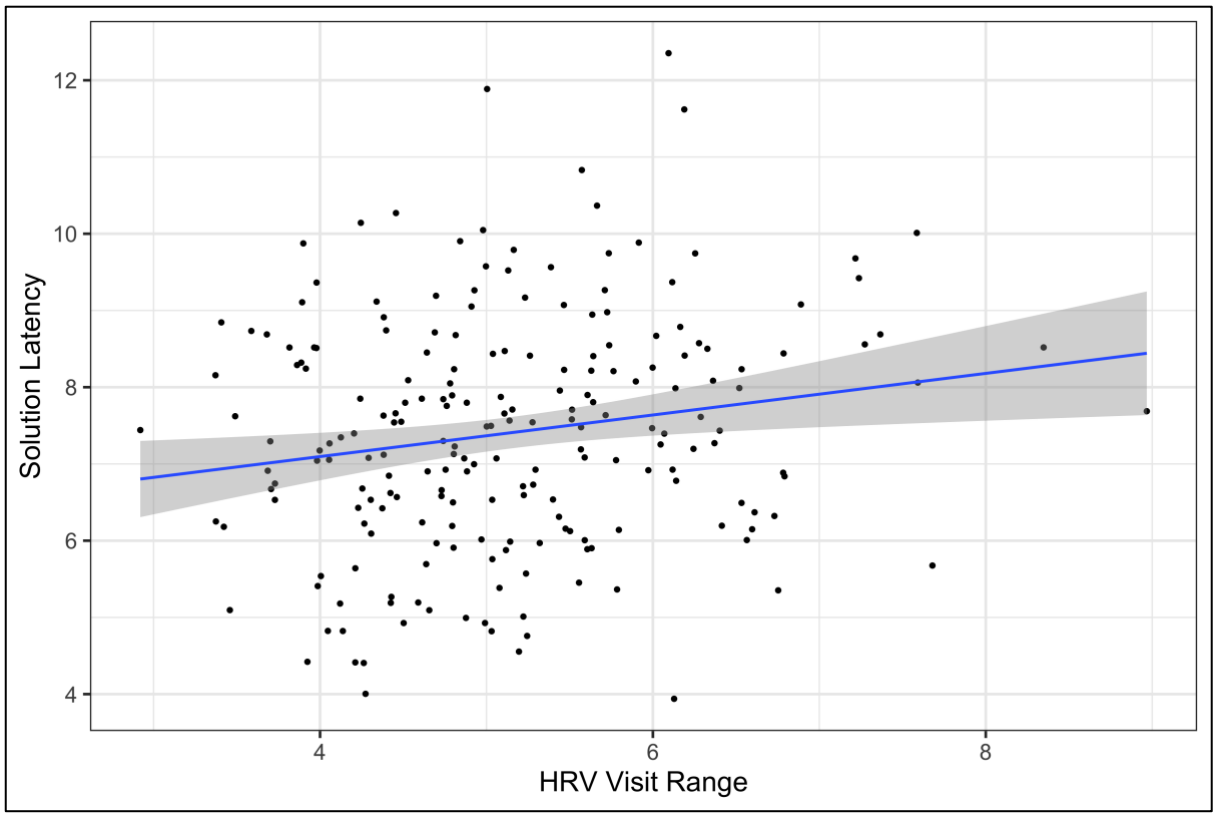

Figure 13. Relationship between HRV visit-range and Solution Latency on the Anagrams task. The positive association indicates that individuals with a larger range took longer to solve anagrams on average.

Table 14

Relationship Between HRV Visit-range and Performance Measures

Task	Outcome	Estimate	p
AX-CPT	Accuracy	-0.108	0.808
	RT	6.176	0.229
Anagrams	Accuracy	-1.016	0.404
	SL	0.198*	0.006

Note: RT = Reaction Time, SL = Solution Latency. Models testing for a relationship between task-range and Accuracy controlled for Education, while models predicting RT and SL controlled for Accuracy (estimates for control variables not shown).

Physiological Variables. Linear regression was also used to estimate the relationship of Age, Sex, and BMI with HRV visit-range. Results from this model can be found in Table 15. BMI was significantly, positively associated with HRV visit-range ($B = 0.162$, $p = 0.017$).

Sex was significantly associated with HRV Range such that males tended to have higher HRV visit-range values (B = 0.304, p = 0.030). Theses associations are plotted in Figure 14.

Table 15

Regression Predicting HRV Visit-range

Effect	Estimate	SE	*p*
Intercept	-0.118	0.09	0.180
Age (Years)	0.079	0.07	0.249
BMI	0.162*	0.14	0.017
Sex (Male)	0.304*	0.07	0.030

Note. Values for all variables aside from Sex were scaled to have a mean of 0 and standard deviation of 1 prior to performing the regression. Sex was a binary categorical variable (Female vs. Male), where Female was used as the reference category. * = $p < 0.05$.

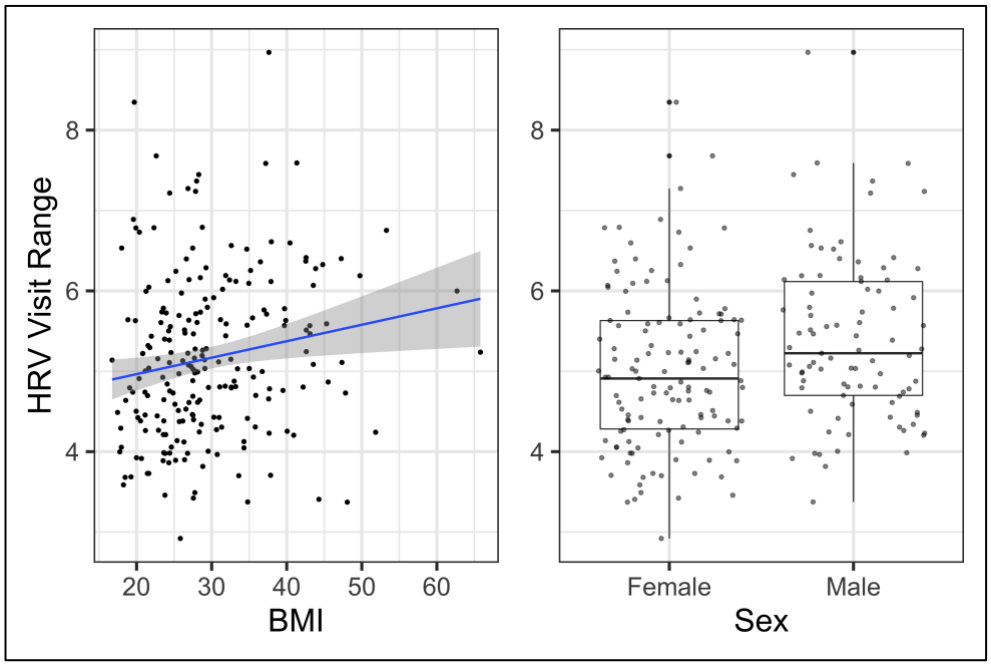

Figure 14. Associations of BMI and Sex with HRV visit-range. On average, higher BMI was associated with a larger visit range and males had higher visit-ranges relative to females. The finding for sex should be interpreted with caution, as males and females completed the tasks in a different order.

Range-Corrected HRV

HRV Range data was next used to perform range-correction on the HRV measures. Before using these RC-HRV values to re-run the between-person models, raw and RC-HRV

values were compared to demonstrate to effects of range correction on HRV measures. For each of the cognitive challenge tasks, the raw HRV and RC-HRV measures were scaled to have a mean of 0 and standard deviation of 1 to allow for comparison of the values. Correlations between raw vs. range-corrected HRV are presented in Table 16, ranging from $r = 0.53$ to $r = 0.97$. A visualization of these relationships can be found in Figure 15.

Table 16

Correlations Between Raw and RC-HRV Between-person HRV Measures

Task	Measure	*r*
AX-CPT		
	Baseline HRV	0.63
	HRV Reactivity	0.97
	On-Task HRV	0.54
Anagrams		
	Baseline HRV	0.59
	HRV Reactivity	0.97
	On-Task HRV	0.53

Note: All correlations were significant at the $p < 0.01$ level

Effect of using RC-HRV on findings

All between-person models were repeated using RC-HRV values, and two cases were found where substantive findings differed depending on whether raw or range-corrected HRV values were used. Interestingly, these two cases differed in terms of whether raw or RC-HRV values were related to performance. Higher baseline HRV predicated faster Reaction Times on the AX-CPT task, but only when RC-HRV values were used (see Table 17). In contrast, the significant association that has been found between on-task HRV and Solution Latency on the Anagrams task that had been found using raw HRV values was not significant when RC-HRV was used (see Table 18). Within-person models were also repeated using on-task

RC-HRV in place of raw HRV reactivity values. Trial-level RC-HRV was negatively associated with log-odds of Accuracy (see Table 19) and positively associated

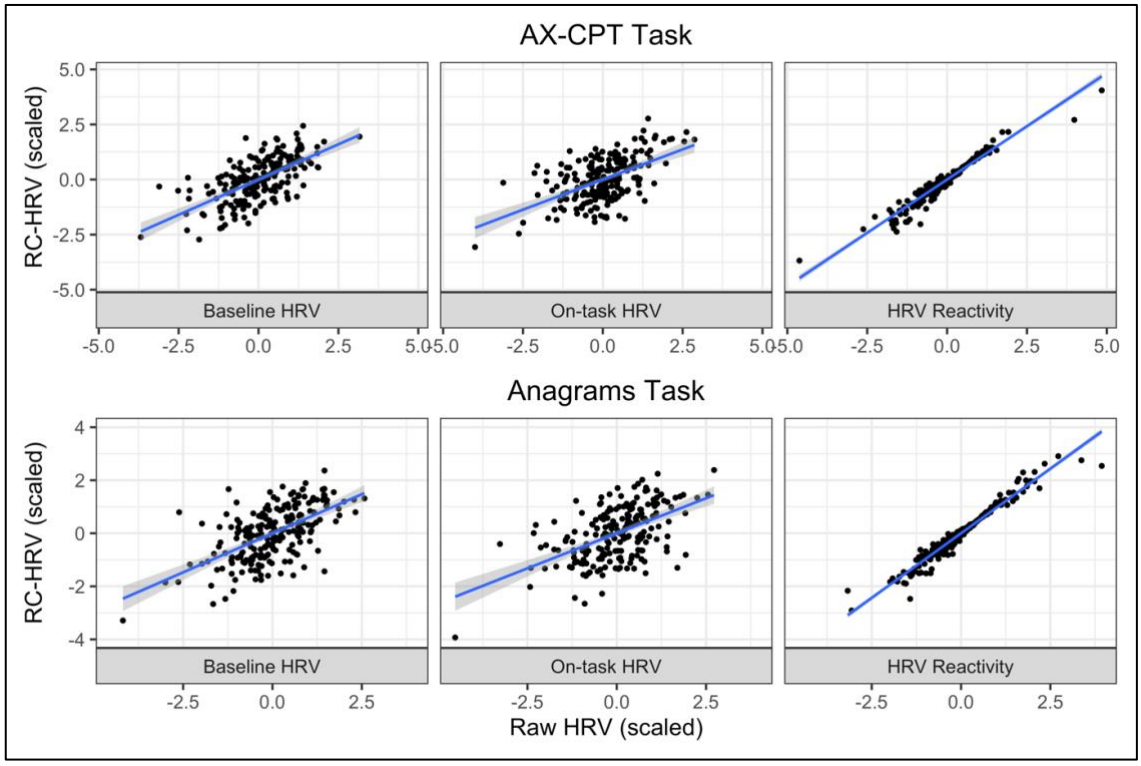

Figure 15. Scaled values of the raw (x-axis) and Range Corrected (y-axis) HRV measures for the AX-CPT (top panel) and Anagrams (bottom panel) tasks. As expected, in all cases there was a strong linear relationship between raw and Range Corrected values.

Table 17

Estimating AX-CPT Reaction Time using raw and RC Baseline HRV

HRV	Term	Estimate	Std. Error	p	Adjusted R^2
Raw					0.046
	Intercept	>0.000	0.070	1.00	
	Accuracy	0.234*	0.071	0.012	
	Baseline HRV	-0.057	0.071	0.467	
RC					0.065
	Intercept	>0.000	0.069	1.00	
	Accuracy	0.188*	0.070	0.001	
	Baseline HRV	-0.149*	0.069	0.034	

Note: * = $p < 0.05$.

Table 18

Estimating Anagrams Solution Latency using raw and RC On-task HRV

HRV	Term	Estimate	Std. Error	p	Adjusted R^2
Raw					0.522
	Intercept	>0.001	0.047	1.000	
	Accuracy	-0.711*	0.048	>0.001	
	On-Task HRV	-0.107*	0.048	0.025	
RC					0.512
	Intercept	>0.001	0.048	1.000	
	Accuracy	-0.733*	0.049	>0.001	
	On-Task HRV	-0.048	0.049	0.322	

Note: * = $p < 0.05$

Table 19

Predicting Trial-Level AX-CPT Accuracy using RC-HRV

Type	Terms	Estimate	95% CI
Fixed Effects			
	Intercept	2.121*	[1.831, 2.416]
	Education: SD	0.396*	[0.044, 0.749]
	Education: Post SD	0.480*	[0.140, 0.822]
	Trial Type (AY)	-1.064*	[-1.185, -0.943]
	Trial RC-HRV	-0.115*	[-0.181, -0.050]
Random Effect			
	Intercept	0.763	[0.675, 0.867]

Note: All continuous values were scaled to have a mean of 0 and sd of 1. * = $p < 0.05$

with Reaction Time on the AX-CPT task (see Table 20). In other words, *lower* RC-HRV during an AX-CPT trial was associated with responses that were both faster and more accurate. In contrast, *higher* RC-HRV during an Anagamas task trial was associated with responses that were faster and more accurate (see Table 21 & 22). These results both matched the findings from within-person models using raw HRV reactivity values to predict performance and were in line with the predictions of the Neurovisceral heuristic depicted in Figure 1.

Table 20

Predicting Trial-Level AX-CPT RT using RC-HRV

Type	Terms	Estimate	95% CI
Fixed Effects			
	Intercept	-0.073*	[-0.14, -0.005]
	Accuracy	0.111*	[0.044, 0.179]
	Trial Type (AY)	0.594*	[0.557, 0.632]
	Trial RC-HRV	0.025*	[0.007, 0.042]
Random Effect			
	Intercept	0.834	[0.825, 0.843]
	Residual	0.474	[0.427, 0.524]

Note: All continuous values were scaled to have a mean of 0 and sd of 1. * = $p < 0.05$

Table 21

Predicting Trial-Level Anagrams Accuracy using RC-HRV

Type	Terms	Estimate	95% CI
Fixed Effects			
	Intercept	0.379^{+}	[-0.072, 0.828]
	Education: SD	1.092*	[0.562, 1.627]
	Education: Post SD	0.720*	[0.206, 1.238]
	Trial Type (Medium)	-1.008*	[-1.134, -0.883]
	Trial Type (Hard)	-3.936*	[-4.181, -3.680]
	Trial RC-HRV	0.234*	[0.156, 0.313]
Random Effect			
	Intercept	1.236	[1.103, 1.391]

Note: All continuous values were scaled to have a mean of 0 and sd of 1. * = $p < 0.05$

Table 22

Predicting Trial-Level Anagrams SL using RC-HRV

Type	Terms	Estimate	95% CI
Fixed Effects			
	Intercept	0.001	[-0.053, 0.055]
	Accuracy	-0.390*	[-0.442, -0.338]
	Trial Type (Medium)	0.284*	[0.226, 0.342]
	Trial Type (Hard)	1.086*	[0.920, 1.252]
	Trial RC-HRV	-0.102*	[-0.135, -0.068]
Random Effect			
	Intercept	0.263	[0.221, 0.304]
	Residual	0.884	[0.863, 0.904]

Note. All continuous values were scaled to have a mean of 0 and sd of 1. * = $p < 0.05$

Discussion

This dissertation was primarily concerned with testing whether PNS regulation was associated with cognitive regulation, and whether such an association manifested differently across two different task types. Due to the functional and anatomical links between the PNS and central nervous system structures which underlie cognition (Thayer & Lane, 2009; Arnsten, 2009), it was predicted that lower HRV during a rapid-response task would predict better performance, whereas higher HRV during completion of a deliberative task would predict better performance. These hypotheses were tested at the between and within-person level using traditional measures of HRV. Between-person results were in partial agreement with the Neurovisceral heuristic model presented in Figure 1. Task type did not moderate the association between either HRV reactivity or on-task HRV with Accuracy but did moderate the relationship of these PNS measures with reaction time/solution latency. Within-person results were more uniformly in agreement with hypotheses. Lower HRV during completion of the rapid-responding task was associated with better performance, whereas higher HRV was associated with better performance on the deliberative task. In addition, there was evidence at both the between and within-person level that baseline HRV moderated the relationship between HRV reactivity and task performance. Implications of the between and within-person findings, as well as the fact that these findings differed, are considered in further detail below. Following the discussion of between and within-person findings, the implications of two additional sets of analyses investigating within-person HRV range will be discussed. HRV range was examined as both a novel measure of PNS regulation and in order to examine the effects of range-correcting HRV data on substantive findings, with somewhat equivocal results suggesting more research into within-person HRV range is warranted.

Contributions of PNS Regulation to Cognitive Regulation

Between-Person Evidence

Results from the present study are consistent with the idea that an individual's level of PNS activation during the performance of a cognitive task contributes to how well they are able to meet task demands. At the between-person level, this was suggested by the finding that both of the HRV measures taken concurrently with task performance (HRV reactivity and on-task HRV) were associated with Solution Latency on the Anagrams Task. The direction of these associations was also in line with the prediction that higher HRV would be associated with better performance on a deliberative task. The association between HRV reactivity and Solution Latency was negative, meaning that decreasing HRV from baseline levels was associated with taking longer to solve anagrams, while increasing HRV from baseline was associated with solving anagrams more quickly. On-task HRV was also negatively associated with Solution Latency, meaning that higher HRV during the task was associated with solving anagrams more quickly. The association between higher HRV and faster solutions on this deliberative task may represent the fact that increased PNS activity co-occurs with a shift in central nervous system activity that facilitates cognitive deliberation (Thayer & Lane, 2009).

These findings add to the existing literature in two ways. First, it adds to existing evidence that on-task HRV during cognitive task performance may be a meaningful psychophysiological measure (Duschek et al., 2009), and that future studies should incorporate this measure along with the more commonly used baseline HRV and HRV reactivity measures. Second, while other studies have examined HRV during anagram performance (Segerstrom & Nes, 2007; Crouch et al., 2015), this is the first study to specifically measure the relationship between HRV and anagram solution latency. The novel anagram task developed for this study required participants to generate solutions on each trial, in contrast to many of the tasks that have been traditionally been used to study links between PNS activity and cognitive task performance that instead require participants to rapidly choose between a pre-determined set of behavioral responses. As explained above, the

use of such a deliberative task has been rare in studies of PNS and cognitive regulation but allows for unique hypothesis to be tested relative to rapid-responding tasks.

In contrast to many previous findings, there was no direct association between baseline HRV and any of the task performance measures. One potential explanation for this discrepancy is the specific performance measures that were used in the current study. Several studies which have found baseline HRV to be related to cognitive task performance measures either did not use Accuracy and/or Reaction Time as outcomes, or, did include them and found no association. For example, Williams and colleagues (2016) found that higher baseline HRV predicted less variability in reaction time on a target detection task, but was not directly related to either accuracy or reaction time. Similarly, another study found that higher baseline HRV predicted greater stability in Stroop task performance across several conditions but was not directly related to accuracy or reaction time (Spangler & McGinley, 2020). Another study that used a CPT found higher baseline HRV to be associated with a greater perceptual sensitivity (derived as the ratios of false positive to false negative responses), but it was not related to measures of reaction time and an association with overall accuracy was not tested (Suess et al., 1994). These findings suggest that between-person differences in baseline PNS activity may be associated with aspects of cognitive regulation that are not captured by accuracy and reaction time measures.

However, while other studies have also found no association between baseline HRV and cognitive task performance (Duschek et al., 2009, Stenfors et al., 2016; Oliveira Matos et al., 2019), several studies have found higher baseline HRV to specifically predict greater levels of accuracy and/or faster reaction times on cognitive challenge tasks (Hansen et al., 2003; Mathewson et al., 2010; Capuana et al., 2014; Colzato & Steenbergen, 2017). The discrepancy between those findings and the current study may be explained in part by different methodological choices. For example, the study by Hansen and colleagues (2003)

grouped individuals into either a “high HRV” or “low HRV” group based on a median split of baseline HRV data, and tested for between-group differences in task performance rather than a linear relationship. This practice has been criticized on statistical grounds (MacCallum, Zhang, Preacher, & Rucker, 2002), and baseline HRV is now typically treated as a continuous rather than a dichotomous variable in contemporary research. Another potential methodological difference that may explain the discrepancy between current and past findings is that the study by Colzato & Steenbergen (2017) relied on time-domain measures of HRV rather than the frequency domain measures used here. While time-domain and frequency domain measures of HRV are highly correlated (Grossman, van Beek, & Wientjes, 1990), studies utilizing both measures have found that findings may differ depending on which type of HRV measure is used (Stenfors et al., 2016). And despite the continued popularity of time-domain HRV measures, it has been argued that frequency domain measures are thought to provide more accurate estimates of PNS activity (Porges, 2007).

Another important difference is that each of three studies mentioned above that found baseline HRV to predict accuracy and/or reaction time used a five-minute baseline period. The current study relied on one-minute baseline measures which may have been an insufficient period of time for participants to enter a relaxed physiological state, although the study by Duschek and colleagues (2009) also used a five-minute baseline period and did not find baseline HRV to be related to task performance. The current study also has a much larger sample size than the studies cited above, which ranged from as few as 17 (Capuana et al., 2014) to 88 (Colzato & Steenbergen, 2017) leaving them more susceptible to Type 1 error (or “false-positives”). At the same time, it is notable that the *direction* of the relationship between baseline HRV and performance measures found here matched that of previous studies, with a positive association between baseline HRV and accuracy measures, and a negative association with Reaction Time/Solution Latency. While none of these between-person

associations reached significance, the association between higher HRV and faster Anagram Solution Latencies was nearly significant ($p = 0.052$; see Table 7). Furthermore, the association between negative HRV reactivity and shorter Anagram Solution Latencies only reached significance when controlling for baseline HRV. Thus, while the current findings differ from previous studies that found a direct relationship between baseline HRV and task performance, they do not suggest that baseline HRV is uninformative as a psychophysiological variable.

Further evidence that baseline HRV was related to cognitive regulation, albeit indirectly, was provided by the finding that baseline HRV moderated the association between HRV reactivity and Anagram Solution Latency. That fact that baseline HRV would moderate the association between reactivity and task performance is in line with an optimal arousal framework (Yerkes & Dodson, 1908; Hebb, 1955; Teigen, 1994), which predicts that decreases in PNS activity may facilitate task performance among individuals with high baseline HRV by increasing arousal, whereas increases in PNS activity may facilitate task performance among individuals with low baseline HRV by decreasing arousal. However, as depicted in Figure 10, increases in HRV from baseline were associated with shorter Solution Latencies regardless of baseline HRV level. Furthermore, the strength of this association was greater among individuals with higher baseline HRV. In other words, individuals who had higher HRV prior to the task benefitted the most from *increases* in HRV during the task. This finding is somewhat counter-intuitive, as it might be expected that individuals with higher baseline HRV are already in a state of elevated PNS activation and thus have not need for further increases in the context of a deliberative challenge task.

While this pattern of moderation differed from expectations, it is in line with previous findings that positive HRV reactivity may be a more effective form of PNS regulation among individuals with higher levels of baseline HRV (Cribbet et al., 2011). One interpretation of

this finding is that, rather than directly contributing to task performance, levels of baseline PNS activity may indicate the strength of the integration of the PNS and brain regions that underlie cognitive regulation (Thayer & Lane, 2009). Thus, the association between PNS regulation and cognitive regulation may be stronger among individuals with higher baseline PNS activity, which manifests at the between-person level as a stronger relationship between HRV reactivity and task performance. The results of the two within-person models that found evidence of baseline moderation are also consistent with this interpretation. For both AX-CPT Reaction Time and Anagram Solution Latency, higher levels of baseline HRV were associated with a stronger relationship between HRV reactivity and performance (see Figure 11 and Figure 12). Thus, across the three findings of baseline HRV moderation, higher baseline HRV seems to be associated with a tighter coupling between PNS and cognitive regulation, regardless of whether PNS regulation manifests and positive or negative HRV reactivity on a given task.

Within-Person Evidence

Despite the interesting between-person findings regarding Anagram Solution Latency, between-person HRV measures were unrelated to Accuracy on either task and AX-CPT Reaction Times. In contrast, results from the within-person models suggest that PNS regulation contributed to both accuracy and speed (Reaction Time/Solution Latency) on each of these tasks. The fact that these associations manifested at the within but not between-person level is notable, given that the majority of the research linking PNS and cognitive regulation to date has been conducted at the between-person level. This raises two related but distinct questions; 1. Why do the between and within-person findings differ? and 2. Why do these associations manifest specifically at the within-person level?. For the first question, the expectation that between-person associations will generalize to the within-person level only holds for processes that meet a specific set of criteria, one of which is stationarity over time

(Molenaar, 2004). Spectral measures of HRV, as were used in this study, are typically characterized by periods of non-stationarity (Weber, Molenaar, & van der Molen, 1992), and speaking more generally it is well established that between and within-person associations often differ, particularly within psychological and psychophysiological studies (Kievit, Frankenhuis, Waldorp, & Borsboom, 2013; Schwerdtfeger & Gerteis, 2014). Thus, it is not surprising that between and within-person associations differed, but the fact that within-person associations were stronger warrants further discussion.

There are conceptual as well as methodological reasons that may explain why associations between HRV and task performance were more apparent at the within-person level. Conceptually, the biological systems that underlie PNS and cognitive regulation are incredibly complex and characterized by person-specific idiosyncrasies due to factors such as genetics, developmental history, etc. (Porges, 2007; Arsten 2009). Focusing on associations between PNS and cognitive regulation at the within-person level accounts for the uniqueness of individuals by modeling these processes as variability around person specific levels of task performance (random intercepts) and trial-level deviations around person-specific levels of baseline PNS activity. The biological systems that underlie physiological and cognitive regulation are also literally embedded within individuals, and thus the individual is the most logical unit of analysis for examining the interplay between these regulatory processes. Other studies have also modelled PNS regulation as a within-person process, with findings that suggest this is an appropriate approach for examining the association between individuals' patterns of PNS regulation and other regulatory processes. For example, within-person coupling of PNS and sympathetic nervous system regulation has been demonstrated using a similar multilevel approach as was employed in the current study (Gatzke-Kopp et al., 2020). Dyadic coupling of PNS regulation across individuals has also been demonstrated by modeling two individual's within-person fluctuations in HRV during an interaction and

studying their correlation over time (Lunkenheimer, Brown, & Fuchs, 2021). Thus, conceptual considerations as well as empirical evidence support the notion that associations between PNS regulation and other regulatory processes are best modeled at the within-person level.

Methodologically, two differences regarding how HRV was quantified at the between vs. within-person level may explain why PNS/cognitive regulation manifested more strongly for the within-person models. The first is the timescale at which HRV and task performance were measured. A single trial-level HRV measure was between 5 and 15 seconds long, and thus trial-to-trial variability in HRV was quantified on the time scale of seconds. In contrast, the HRV measures used in the between-person models were taken on the time scale of minutes. Given that the PNS is a fast-acting system capable of responding to changes in the environment in real time (Berger, Saul, & Cohen, 1989; Grossman & Taylor, 2007), this faster timescale of the within-person HRV measures may more accurately capture the process of PNS regulation. Likewise, trial-measures of task performance may better reflect the continuous process of cognitive regulation than average performance across the entire task. Measuring processes on the appropriate timescale is critical for quantifying how they unfold over time (Shannon & Weaver, 1949), and the ability to do this is one advantage offered by a multilevel modeling approach. In addition to the faster time-scale of measurement, the within-person models used here utilized many more data points per individual to quantify PNS and cognitive regulation relative to the between-person models. Given that the interest of the current study was the relationship (slope) between HRV and task performance, the higher number of data points per individual in the multilevel models meant that these within-person studies had significantly higher statistical power than the between person models (Snijders, 2005).

The fact that associations between PNS and cognitive regulation were stronger at the within-person vs. between-person level was in line with our hypotheses. Furthermore, the nature of each of the associations between HRV trial reactivity and task performance were in line with the heuristic model presented in Figure 1. Specifically, more negative HRV reactivity predicted a higher probability of accuracy and faster reaction times across AX-CPT trials, as would be expected if lower PNS activity contributes to a cognitive state that is optimal for rapid behavioral responding in the contexts of choosing between two simple response options. In contrast, more *positive* HRV reactivity predicted a higher probability of accuracy and faster solutions across trials of the Anagram task, as would be expected if higher PNS activity contributes to a cognitive state that is optimal for the more deliberative process of generating and choosing between more complex behavioral responses. There are two important considerations regarding these sets of findings. First, each of these findings supports the idea that PNS regulation contributes to cognitive regulation based on the fact that HRV measures predicted task performance. Second, these findings further suggest that the specific nature of PNS regulation differed between tasks, with decreases in HRV reflecting optimal regulation in the context of a rapid-response task and increases in HRV reflecting optimal regulation in the context of a deliberative task.

Together, these findings provide strong evidence that different levels of PNS activity facilitate different kinds of cognitive processes, and are in line with the prediction that such associations are due to concurrent changes in central nervous system activity that accompany changes in PNS activation (Thayer & Lane, 2000; Thayer & Lane, 2009). However, it is important to note that the current study did not involve any direct measures of brain activity. Thus, while findings were consistent with the neuroanatomical predictions of Polyvagal and Neurovisceral Integration Theory, it was assumed rather than demonstrated that HRV measures correspond to activity levels in the prefrontal cortex. Other studies have provided

more direct evidence for this link (Thayer, Ahs, Fredrikson, Sollers III, & Wager, 2012; Gatzke-Kopp et al., 2020), and decades of animal research that demonstrate functional anatomical connections between vagal fibers of the PNS and central nervous system structures that underlie cognitive regulation (Burn, 1950; Sawchenko, 1983; Bennaroch, 1993). Future studies in humans would benefit from simultaneously measuring HRV, prefrontal activation, and cognitive task performance, in order to test each aspect of the heuristic model in Figure 1. Such a program of research would improve our understanding of how peripheral physiological measures correspond to central nervous system activation, which is a major goal of psychophysiological research.

An additional set of findings from the within-person models was that baseline HRV moderated the association between HRV reactivity and both AX-CPT Reaction Time and Anagrams Solution Latency. Similar to the baseline HRV moderation finding from the between-person models, each of these within-person models found that higher levels of baseline HRV were associated with a stronger association between HRV reactivity and task performance. Specifically, decreases in HRV from baseline predicted faster Reaction Time on the AX-CPT task, and the strength of this association increased with higher levels of baseline HRV. Likewise, increases in HRV from baseline predicted shorter Solution Latencies on the Anagrams task, with the strength of this association increasing with higher baseline HRV. The fact that higher baseline HRV predicted a stronger coupling of HRV reactivity and task performance across both tasks is notable, given that the direction of the association differed by tasks. Thus, the current findings suggest that, regardless of whether successful PNS regulation involves increasing or decreasing PNS activity, higher baseline PNS activity predicts a stronger association between PNS and cognitive regulation.

The fact that this finding was true for Reaction Time and Solution Latency but not Accuracy may suggest that higher the moderating role of Baseline HRV is specific to

measures of how quickly individuals responded to trials. This interpretation is in line with the proposal that higher baseline HRV is a marker of more efficient cognitive regulation (Thayer, 2006), which would facilitate faster solutions. However, the trial-level Accuracy measures also differed from measures of Reaction time and Solution Latency in important ways. First, trial level Accuracy was modelled as a binary outcome (either accurate or inaccurate), whereas the other trial level performance measures were continuous. This required the use of logistic models for the multilevel models predicting trial-level Accuracy, which have lower power for detecting cross-level interactions relative to continuous models (Schoeneberger, 2016). The Accuracy measures for each task were also characterized by less within-person variability than their respective temporal performance measures, which may have further impeded the ability to detect interaction effects in the models predicting trial-level Accuracy. Thus, the lack of a moderation effect for the Accuracy models may be due to statistical factors rather than a true difference in how baseline HRV moderates the relationships between HRV reactivity and temporal vs. accuracy measures. Future studies could address this issue by using a higher number of trials per task to increases statistical power for detecting within-person associations, and/or using tasks with greater within-person variability in trial-level Accuracy. For example, a version of the Anagrams task used in the current study with more trials and a higher proportion of difficult anagrams may provide data that is better able to elucidate interaction effects when predicting Accuracy.

Within-Person HRV Range

Within-person HRV range was calculated at the task level as a measure of net intra-individual variability, which may provide unique information about regulatory processes relative to traditional measures of change such as reactivity (Ram & Gerstorf, 2009). However, there was no association between HRV task-range and any of the performance outcomes and thus no difference between these associations across tasks. This is in line with

previous studies which found that within-person standard deviations of HRV were unrelated to cognitive task performance (Spangler et al., 2018; Spangler & McGinley, 2020). One explanation for these null findings is that intra-individual variability measures of physiology may be inappropriate for use as a predictor of static measures of task performance, such as mean accuracy or reaction time. For example, the studies by Spangler and colleagues (2018; 2020) found that within-person standard deviations of HRV during task performance were related to within-person *standard deviations* of performance measures across task conditions, but not performance measures themselves. Interestingly, another study found that a static measure of HRV (baseline HRV) was predictive of intra-individual variability in reaction time on a target-detection task (Williams et al., 2016). Thus, while the current findings suggest that HRV task-range is not associated with cognitive regulation as measured by task performance, further study of intra-individual variability measures of both physiology and task performance appear warranted.

Within-person HRV range was also calculated at the visit level, which incorporated measures from a variety of experimental tasks that varied in terms of social context and cognitive demands. It was expected that exposure to this range of measurement contexts would induce both decreases and increases in PNS activation, such that each person's HRV range across these contexts would reflect their full range of normative HRV values. HRV visit-range was examined for an association with task performance measures and physiological variables, in order to determine whether within-person HRV might reflect individual differences in psychophysiological regulation, or instead reflect more "purely" physiological differences. HRV visit-range was positively associated with Solution Latency on the Anagrams task. This finding – that individuals with larger HRV ranges took longer to solve anagrams on average – was unexpected in two ways. First, it was hypothesized that between-person difference in HRV visit-range would not be related to task performance.

Second, if an association were found it was expected that larger HRV visit-ranges would reflect a greater capacity for PNS regulation and thus be associated with better cognitive regulation. However, given the novelty of this measure of within-person HRV range, as well as the fact that range was unrelated to three of the four performance measures, additional evidence is needed to determine whether within-person HRV range across multiple tasks is a meaningful psychophysiological measure.

It was also found that HRV visit-range was positively associated with BMI and also higher on average among males. This suggests that between-person differences in within-person HRV range may be related to physiological factors. For example, there may be greater regulatory demands on the PNS among higher BMI individuals and/or males in terms of maintaining physiological homeostasis of peripheral organs like the heart. If this were the case, HRV range may reflect individual differences in physiological but not psychophysiological regulation. However, the finding that HRV range was higher among males should be interpreted with caution, given that males and females completed experimental tasks in a different order, and in some cases completed different tasks altogether. Together, these findings suggest that within-person HRV range measured across a range of contexts may reflect psychophysiological regulation as well as more purely physiological factors. It is also possible that within-person HRV range as measured here reflected idiosyncratic fluctuations in PNS activity rather than a measure of PNS regulation. Repeated measures of HRV range within a single day taken repeatedly over multiple days would allow for an assessment of whether HRV range reflects a stable trait-like variable or a more transient variable. However, the current findings demonstrate that, in principle, there were sufficient between-person differences in within-person range for it to be used a dependent variable.

HRV Range Correction

In light of previous studies suggesting that physiological measures may benefit from range-correction (Lykken et al., 1966; Bush et al., 1993), and in keeping with the idea that HRV may not be an invariant marker of PNS activity across individuals, the between and within-person models were re-run after applying range-correction to HRV measures. In contrast to expectations, the use of RC-HRV measures did not lead to more significant findings for the between-person models, nor was it associated with a reduction in standard errors for the estimated relationships between HRV performance measures. The use of RC-HRV values for the within-person models allowed trial-level HRV values to be used in place of HRV reactivity, as RC-HRV is already expressed as a within-person variable. However, substantive findings did not differ between models using HRV reactivity and trial level RC-HRV. Findings for the between-person models were equivocal in terms of how the use of RC-HRV affected substantive findings. The significant association between higher On-task HRV and shorter Solution latencies that had been found using raw HRV values on the Anagrams task was not significant when RC-HRV values were used. In contrast, raw baseline HRV was unrelated to AX-CPT reaction times, but a significant negative association was found when RC-HRV was used. For the within-person models, substantive results did not differ between models using raw baseline and reactivity HRV measures relative to models using RC-on-task HRV.

Limitations and Future Directions

This study has several limitations that should be noted. First, participants were primarily white, higher-income, and in most cases highly educated, reflecting the demographics of many communities located near large research universities. Given evidence that psychophysiological findings do not necessarily generalize across different racial and/or socioeconomic groups (Gatzke-Kopp, 2016), it cannot be ruled out that the current findings are unique to this type of sample. Another limitation is that, because this study was part of a

larger study of self-regulation in children and parents, all of the participants were parents and the majority were also married. This may limit generalizability as there are likely to be selection effects which differentiate individuals who choose to marry and have children from those that do not, and both parental status and marital status have been found to correlate with a number of psychological and physiological factors (Helbig, Lampert, Klose, & Jacobi, 2006; Willitts, Benzeval, & Stansfeld, 2004). At the same time, much of the previous research relating PNS and cognitive regulation have relied on undergraduate samples (Duschek et al., 2009; Capuana et al., 2014; Williams et al., 2016; Colzato et al., 2018), and the use of a community sample of parents ranging from 23 to 54 years of age helps to extend this area of research to a unique population.

Another important limitation is that the current study relied on a HRV and task performance measures to infer information about brain activity but did not include any direct neurological measures. The Neurovisceral heuristic presented in Figure 1 depicts simple linear relationships between PNS regulation, cognitive regulation, and brain activity for conceptual clarity, but the true relationship between these factors is likely to be complex and non-linear. The use of such conceptual heuristics can be useful for studying links between neurological and psychological phenomenon but can become impediments to research if they are not continuously supplemented and updated by studies relying on more direct neurological measures (Cromby, 2007). Future studies would benefit from incorporating measures of PNS activity, cognitive performance, and central nervous system activity simultaneously in order to model these associations. In addition, the activity of the sympathetic nervous system has been found to moderate the relationship between PNS and cognitive regulation (Giuliano et al., 2017) and to covary with both central nervous system and PNS activity in complex ways (Gatzke-Kopp et al., 2020). Future studies may benefit from incorporating sympathetic nervous system measures along with PNS and central

nervous system measures in order to more fully examine the relationship between physiological and task performance measures in the context of different types of cognitive challenge tasks.

An additional limitation of the current study is that task performance measures were the sole measure of cognitive regulation. This was based on the assumption that individuals who performed well on a task successfully matched their cognitive state to facilitate task demands, and thus evidenced successful cognitive regulation. While this assumption is defensible, it does not differentiate between potential explanations for poor task performance. Some individuals may have performed poorly on a given task despite engaging in cognitive effort, while others may have had the capacity to perform well but were not motivated to engage with task demands. This distinction may be important for understanding the interplay of PNS regulation and cognitive regulation, as between-person differences in effort vs. motivation may have different physiological manifestations. Future studies may benefit from combing subjective ratings of effort and motivation from participants with physiological and task performance measures.

Despite these limitations, findings from the current study may help to inform future research of PNS and cognitive regulation. Two major implications are as follows. First, these findings strongly support the use of more deliberative cognitive tasks in future studies. Second, future studies of PNS regulation should consider measuring PNS activation in such a way that allows for within-person analyses to be performed. In the current study, this was facilitated in part by relying on second-by-second estimates of HRV, which can now be derived relatively simply thanks to advances in software (Martínez et al., 2017). The implications of the findings related to within-person HRV range are less straightforward, and further study is needed to determine if HRV range may be a useful psychophysiological measure. Likewise, our findings regarding range-correction did not suggest that it leads to

more accurate estimates of within-person PNS activity, but did show that substantive findings can differ depending on whether range-correction is applied to HRV measures. Any studies that do apply range-correction to HRV measures (see Pattyn et al., 2008) should provide a justification for doing so, as well as a comparison to uncorrected HRV data.

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Trinity College Dublin: **2013 - 2014**
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PUBLICATIONS & PRESENTATIONS

Cortical and affective regulation of autonomic coordination (Gatzke-Kopp, L.M., Benson, L., **Ryan, P.J.,** & Ram, N., 2020). *Psychophysiology*.

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White, R**., Ryan, P.J.,** Lydon-Staley, D., & Gatzke-Kopp, L. COMT gene variants differentially moderate the effects of physical and interpersonal risk factors on children's delay tolerance. Poster presented at *Society for Research on Child Development Biennial Meeting,* Austin, TX, USA, 2017.