DISSERTATION

HEART RATE VARIABILITY AS A BIOMARKER OF SELF-CONTROL AND ITS RELATIONSHIP WITH DEPRESSION

Submitted by

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ABSTRACT

HEART RATE VARIABILITY AS A BIOMARKER OF SELF-CONTROL AND ITS RELATIONSHIP WITH DEPRESSION

Human behavior is guided by a desire to attain certain goals. Individuals must manipulate the pursuit of multiple goals simultaneously and decide how to navigate their environments to support the desires they most value. Failures of self-control are common and present as psychopathologies characterized by emotional and cognitive dysregulation, namely depression. The relationship between poor self-control and the manifestation of depression is critical to target in order to better predict, understand, diagnose, and treat symptomologies, yet the precise nature of the relationship between self-control and depression is insufficiently understood. The current study employed a novel approach to investigate the relationship between self-control and depression and whether our understanding of that relationship could be improved with the incorporation of heart rate variability (HRV), a robust neurocardiac biomarker of self-control-related abilities. Findings supported the merit of HRV as a biomarker of self-control and revealed that self-control fully mediated the relationship between HRV and depression, although effect sizes indicate that the relationships were weak. It was expected that age played a role in this relationship due to the changing lifespan trajectories of neurocardiac networks interconnected with self-control and depression, although this premise was found to be unsupported. These discoveries deepen our understanding of the neurocognitive and autonomic dynamics of depression and supplicate clinical researchers aiming to decrease dysfunction to entertain approaches supported by a biopsychological perspective.

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CHAPTER 1: LITERATURE REVIEW

"Distinguish between real needs and artificial wants and control the latter."

- Mahatma Gandhi

Overview of the Chapter

Self-control is a function of the prefrontal cortex and is defined as the ability to inhibit behavioral responses that are either inappropriate for the situation or are incongruent with personal goals (Bauer & Baumeister, 2011; Carver & Scheier, 2011). Failures of self-control are common, and people often lose control of their behavior in a variety of contexts (Baumeister & Heatherton, 1996; Baumeister et al., 1994). Impaired self-control is associated with a wide array of psychological disorders, including depression (Strauman, 2017). Despite the extent of self-control dysfunction across syndromes, the exact role that self-control plays in the etiology of disorders has yet to be fully explored (Coyne & Gotlib, 1983; Strauman, 1992). For example, it is unknown if multiple pathways exist that lead to the development of self-control difficulties, or if early biological difficulties with self-control predisposes an individual to later behavioral difficulties and poor symptom management (Strauman, 1992). Due to this high prevalence of difficulties with self-control in psychopathology paired with our incomplete understanding of the development of self-control skills, researchers have tried to identify biomarkers for poor self-control. Biomarkers provide an objective way to characterize dysfunction, and by finding biomarkers, researchers can better predict, diagnose, and monitor signs of impairment (Mayeux, 2004). Investigations that have aimed to identify biomarkers of self-control have traditionally employed behavioral and neuroscientific methods such as EEG and fMRI, but several shortcomings exist with these practices. Both EEG and MRI require equipment, training, and

analysis tools that are expensive, which may limit the practicality of the methods in laboratory settings. Furthermore, the high heterogeneity of behavioral tasks calls into question the validity of claims that correlate performance with fMRI and EEG variations. Researchers have thus begun to explore other means to identify biomarkers of self-control through cardiovascular measures. One such cardiovascular measure is heart rate variability. Heart rate variability (HRV) refers to the beat-to-beat variation in heart rhythms and is reflective of the heart's ability to respond to persistently changing environmental demands. High HRV is associated with a healthy ability to adapt to the environment, and low HRV is associated with a decreased ability to respond to external demands (Thayer et al., 2012).

The structures and functions that are involved in the body's response to stress overlap with the mechanisms that generate HRV and those associated with self-control (Kemp & Quintata, 2013). By studying the stress response, researchers can learn how this system connects to autonomic functions and how unhealthy patterns may relate to depression (Hartmann et al., 2019). As part of the response to threat, prefrontal abilities (i.e., executive functions) are needed to properly assess the validity of a detected environmental threat and adopt an appropriate behavioral response or change as needed (Morawetz et al., 2017). Part of this behavioral response entails self-control, which allows the individual to manipulate several simultaneously occurring goals and inhibit behavioral responses that are either inappropriate for the situation or non-congruent with personal goals (Thayer & Siegle, 2002). The detection of a threat influences changes in HRV, as the heart rate increases in the presence of a threat and decreases in the absence of a threat or once the threat is resolved. Low HRV, or an inability to adapt one's physiological state to the environment, is associated with a predisposition to chronic threat perception, amygdala hyperactivation, and a propensity towards negatively biasing ambiguous

cues (Segerstrom & Nes, 2007). These three factors parallel those indicated in the etiology of depression, as outlined in more detail in further sections (Koster et al., 2011; Strauman, 2017).

Further evidence suggests that age plays an important role in the relationship between HRV, self-control, and depression. Specifically, age appears to be a factor that may strengthen or weaken the relationship between HRV and self-control (Holzman & Bridgett, 2017) and thus may serve as a distal variable in the development of depression. Increased age is associated with both lower HRV and lower PFC self-control abilities due to functional connectivity changes in neurocardiac networks (Fukusaki et al., 2000; Sakaki et al., 2016; Sowell et al., 2004).

Although the factors of HRV, self-control, age, and depression are associated with one another, they had yet to be investigated concurrently within a single study. The current study aimed to determine the relationship between these four variables and to determine the validity of HRV as a biomarker for self-control and more distally depression. It was hypothesized that HRV was positively associated with self-control, and that self-control mediated the relationship between HRV and depression. Lastly, it was hypothesized that age moderated the relationship between HRV and self-control, such that increased age increased the effect of HRV on self-control. Examining these constructs together has provided a more comprehensive understanding of how the four are interrelated. A relationship between the four variables would suggest that HRV is a biomarker not only of self-control but may also be considered a biomarker of depression via self-control. Furthermore, an examination of the role of self-control may provide a better understanding of the connection between HRV, age, and depression.

For the remainder of this chapter, a review of the literature pertaining to the potential of heart rate variability as a biomarker of self-control and the variables' relationship with age and depression will be explored. First, the prevalence of poor self-control across psychological

disorders and the challenges of measuring self-control will be discussed. Next, the potential of heart rate variability as a biomarker of self-control will be illustrated with a review of neuroanatomical connections between cortical, subcortical, and autonomic circuits that elicit the body's stress response. The contributions of poor heart rate variability and poor self-control to depression susceptibility will then be weighed. Lastly, discrepancies in the literature pertaining to the relationship between heart rate variability and self-control will be evaluated, with the examination of age put forth as a possible resolution.

Self-control

Human behavior is often guided by a desire to attain a certain status or goal. This objective is achieved through behavior modification and control, the results of which are then evaluated and adjusted as needed (Baumeister et al., 1994a; Baumeister & Heatherton, 1996; Carver & Scheier, 1998; Connell, 2015; Heatherton, 2011). Regulatory processes are continuously engaged to adjust, interrupt, or stop thoughts, feelings, and behavior in an intricate effort to reach personal goals or maintain current standards (Baumeister et al., 1994; Baumeister & Heatherton, 1996; Carver & Scheier, 1998; Heatherton, 2011). To successfully carry out regulatory processes, a person must first have an established or desired goal, they must be able to engage in actions that promote goal attainment, and they must be able to evaluate their progress towards achieving the goal (Baumeister & Vohs, 2003). These abilities engage sophisticated nervous system functions that must operate cohesively to achieve the intended result.

Individuals often experience conflict in the pursuit of their goals and desires, requiring more cognitive resources to manage and choose which goal to pursue. Multiple goals may exist that are incompatible with one another, namely a clash between long-term goals and short-term goals. For example, a person may have a long-term goal of improving their health, but they may

simultaneously experience an immediately gratifying desire to skip going to the gym that day. Here, this person is experiencing conflicting impulses. They must abstain from giving in to immediate gratification if they are to maintain long-term values that they have decided are important to them. Specific regulatory processes that are dispatched in this scenario enable an individual to inhibit undesired behaviors and appropriately respond to situational demands (Heatherton, 2011). This subgroup of regulatory abilities is termed self-control.

Self-control is the regulation of conflicting impulses to promote long-term goals over immediately gratifying ones (Bauer & Baumeister, 2011; Carver & Scheier, 2011). Self-control abilities are engaged when a person must choose between two options that have contrasting goals: one that is only rewarding in the short-term, and the other that is expected to bring greater returns in the long-term. To be a valid test of self-control, the competing impulses must have differing levels of importance and must demonstrate a clash between immediate gratification and long-term values (Carver & Scheier, 2011; Heatherton, 2011). For instance, consider a person with two long-term goals of earning a promotion and being present for their family. They find themselves in a situation in which they must choose between spending time with their children and working late to meet a deadline. While difficult, this dilemma does not demand self-control; these goals are comparably important to the person and neither are only rewarding in the short-term. To illustrate a need for self-control, the scenario could be changed to a decision between going to a bar or working late to meet a deadline. This modified example contains one choice that is only gratifying in the short-term and one that is more valuable in the long-term, respectively. To recap, self-control is defined as the ability to act and engage in behaviors that promote long-term goals over short-term desires. The practice of self-control is the product of a

complex partnership of neurocognitive functions that must continuously adapt to changing situational demands (Bauer & Baumeister, 2011; Carver & Scheier, 2011).

As with any high-level cognitive ability, failures of self-control are common. People often forgo long-term values to pursue immediate gratification in a variety of contexts (Baumeister & Heatherton, 1996; Baumeister et al., 1994). This lack of self-restraint is sometimes defined in the literature synonymously with impulsivity (Connell, 2015). In this framework, impulsivity can be thought of as the converse of self-control, such that impulsivity is the engagement of unplanned or premature behavior without regard for all relevant factors and potential negative consequences (Potenza & de Wit, 2010; Reynolds et al., 2006). Both self-control and impulsivity are multi-dimensional constructs, and as such, they are associated with a number of different theories pertaining to the relationship between each other and their relationship with regulatory processes as a whole. While some theories purport that low self-control is equivalent to impulsivity, others contend that the two constructs uniquely predict behavior (Duckworth & Kern, 2011; Tangney et al., 2004). In the latter model, the importance of how the two constructs interact to either promote or obstruct goal-directed behavior is emphasized. Specifically, one should consider how the strength of the impulse affects an individual's ability to control and regulate the impulse (Connell, 2015). Here, impulsive actions can be defined as succumbing to immediate temptations despite conflicting long-term goals. Impulse strength can be thought of as the degree to which a barrier, either purposeful or not, is successful in causing a person to abandon their long-term values. Impulse regulation is the ability of a person to overcome that barrier to maintain their long-term goal (Connell, 2015). Overall, however, factor analyses indicate that measures of both self-control and impulsivity capture similar concepts and the various theories can be woven into one coherent picture

(Connell, 2015; DeYoung, 2011). The varying conceptualizations of self-control highlight its complexity and forecast difficulties in quantifying this construct with measurement tools.

Theories of Self-control

Understanding how self-control is defined is critical for clinical researchers to implement measures with high validity and to accurately identify areas of dysfunction. This knowledge is especially practical here as there are multiple models that aim to characterize self-control, and some measurements are better than others for capturing specific elements of the construct.

Control Theory

Control Theory examines how specific behaviors are chosen and how those behavioral choices are regulated. The first question refers to the "direction" of the behavior, or how a person considers many options to ultimately select a certain behavior for the context at hand. The second question refers to the person's ability to regulate the "intensity" of the response, or the strength, frequency, and completeness of the behavior (Carver & Scheier, 1981).

To answer these questions, Carver and Scheier (1981) describe the progression of how regulatory processes are carried out and where self-control comes into play to promote goal-directed behavior. The first step in performing a behavior is analyzing and categorizing perceptual information. This input is used to form a goal, or "behavioral standard", which guides decision making towards maintaining or reaching that standard (Carver & Scheier, 1981). Next, a series of cognitive and affective functions operate in a behavioral feedback loop to enable the current state to match the desired standard. The current existing state or behavior is compared to the goal-state in what is termed the first "Test" phase of the feedback loop. If a discrepancy between the current and desired state is identified, the "Operate" phase acts to change the existing state in an attempt to eliminate the discrepancy. Another "Test" phase ensues to

compare the current state to the desired state, and if a discrepancy is still detected, the "Operate" phase is initiated once again. The process cycles through "Test" and "Operate" phases until the current state is consistent with the desired state, at which point the behavioral feedback loop ends in the "Exit" phase (Carver & Scheier, 1981).

In this theory, self-control parallels the "Operate" phase. Self-control is defined as the action of implementing a set of behaviors that best promote the person's goal or desired state. This conceptualization highlights why self-control is an important construct to isolate from other regulatory processes when trying to pinpoint how behavioral dysfunction occurs. A person may be fully aware of the correct response (i.e., determining the "direction" of the behavior to reach a goal), and that there is a mismatch between the desired and present behavior (i.e., the "Test" phase of the behavioral feedback loop), but without self-control (i.e., the "Operate" phase), the person struggles to take action to reach their goal. This ability is especially important when an individual needs to maintain multiple goals during complex decision making and inhibit inappropriate responses (Baumeister & Heatherton, 1996; Baumeister et al., 1994; Heatherton, 2011).

Control Theory proposes that there are cognitive, metacognitive, and affective elements that drive the behavioral feedback loop (Connell, 2015). Cognitive abilities enable a person to categorize and evaluate perceived features in their environment to formulate the goal or standard. Cognitive and metacognitive abilities are implicated in the "Test" phase of the feedback loop, in which there is a comparison between the person's current state and desired goal state to detect discrepancies. Carver and Scheier (1981) propose that self-directed attention is a significant determinant of whether a person employs the "Test" phase. They argue that a person cannot act upon a discrepancy if they do not attend to and are unaware of the discrepancy. In support of this

argument, studies have found that higher levels of self-directed attention are associated with more conformity to behavioral standards that are salient in the person's environment (Beaman et al., 1979; Scheier et al., 1974). Lastly, the "Operate" phase is driven by affective elements (Carver & Scheier, 2011). The theory puts forth that affective processes initiate the behavior needed to resolve the discrepancy, and that these processes determine the strength in which the person propels themselves towards the desired state (Carver & Scheier, 2011; Connell, 2015).

Within the framework of self-control, these ideas combined with other conceptualizations support the notion that the construct is both a cognitive and affective process. Cognitive abilities are necessary to manipulate multiple goals at once and to inhibit inappropriate responses. Sufficient affective functioning plays an important role in the initiation and success of the response in advancing towards a desired goal. Recognizing that self-control is an ability comprised of both cognitive and affective elements provides insight into how psychopathologies characterized by poor affect regulation, such as depression, may be related to self-control.

Limited Resource Model

The Limited Resource Model defines self-control as the ability to inhibit automatic inclinations and sacrifice immediate gratification in order to pursue a long-term goal (Baumeister et al., 1998). This capacity, colloquially referred to as willpower, is considered to be a strength as opposed to being a skill (Bauer & Baumeister, 2011). A person can have strong self-control or weak self-control, or degrees in between the two ends of the spectrum. The strength of a person's self-control is a limited resource. If a person must exert a great deal of self-control in one situation, they will have less self-control in subsequent regulatory attempts within a certain period (Baumeister et al., 1998; Connell, 2015). "Ego depletion" describes self-control failures that result from earlier attempts to regulate behavior (Muraven & Baumeister, 2000). Ego

depletion interferes with attempts to exercise self-control by weakening controlled and deliberate means of achieving a goal, giving way to automatic and thoughtless impulses (Connell, 2015). Indeed, studies report that individuals who have depleted levels of self-control are more likely to choose decision-making strategies that are less effortful and contemplative (Bauer & Baumeister, 2011).

The Limited Resource Model draws parallels between self-control strength and physical muscle strength; repeated exertion of self-control results in self-control fatigue just as repeated exertion of muscles results in muscle fatigue (Muraven & Baumeister, 2000; Segerstrom & Nes, 2007). Furthermore, self-control training strengthens this ability and decreases the occurrence of ego depletion (Connell, 2015; Muraven et al., 1999; Oaten & Cheng, 2006). Clinical researchers have taken advantage of the ability to train self-control by incorporating strength building strategies in various treatments. Studies purport that ego depletion diminishes with strategies such as self-affirmation, relaxation, and positive affect building (Connell, 2015; Schmeichel & Vohs, 2009; Tice et al., 2007, Tyler & Burns, 2008).

Research further indicates that ego depletion is not domain-specific; exerting self-control in one domain may impair a person's ability to practice self-control in other, dissimilar domains (Baumeister et al., 1998; Muraven & Baumeister, 2000). Ego depletion may occur across such diverse domains of performance such as physical endurance, behavioral persistence, emotion regulation, task switching, and impulse restraint (Bauer & Baumeister, 2011; Connell, 2015). For example, if a person has one goal to exercise and another goal to attain a promotion at work, working towards the goal to exercise by consistently going to the gym may hamper their ability to put forth equal effort to maintain their other goal of earning a promotion. In this case, when presented with options to either go to the bar after work or stay late at the office, the person may

be more likely to choose the immediately gratifying option of going to the bar due to their limited self-control resources. Self-control strength is especially important in instances like in the above example. Individuals commonly have multiple long-term goals to maintain and must be able to choose behaviors that promote these goals in the face of tempting yet self-defeating options.

Self-control strength and ego depletion affect goal-oriented decisions by either progressing towards or hindering the attainment of the set goal. Both baseline self-control capacity and prior exercises in self-control contribute to a person's ability to successfully choose behaviors in favor of their long-term goals (Connell, 2015). As with Control Theory, this model supports the notion that self-control encompasses both cognitive and affective processes. Attempts to exert control to pursue goal attainment with cognitive resources may deplete a person's ability to regulate their emotions, and vice versa. Furthermore, a lack of self-control capacity may contribute to hasty behavioral choices and poor emotional regulation commonly associated with depression.

Cognitive Affective Processing System (CAPS)

The CAPS theory posits that a person's ability to pursue long-term goals depends on both the availability of their impulse control strategies and how long it will take to attain the goal. The latter concept is termed "temporal discounting". Temporal discounting is the phenomenon that the subjective value of pursuing a goal or a reward decreases as the time until the goal or reward is attained increases (Mischel & Ayduk, 2011). As an example, if a person is presented with the opportunity to earn $500, they are more likely to pursue that goal if the money will be rewarded tomorrow compared to five years from now. Furthermore, if a person must choose between a reward of $100 tomorrow or $500 in five years, they may be more likely to choose the more

immediate reward, especially if they have poor self-control, even though the sum is significantly less than if they waited.

There are two systems within the CAPS theory that interact to allow a person to maintain self-control: a "hot" emotional system, and a "cool" cognitive system (Metcalfe & Mischel, 1999). The cognitive system is characterized by deliberate, contemplative, and complex decision making, and functions to interpret informational, spatial, and cognitive components of stimuli. The emotional system is implicated in rapid, simple, and emotionally charged decision making. This system functions to reflexively react when triggered by certain stimuli and is evolutionarily adaptive for quick fight or flight responses (Connell, 2015; Metcalfe & Mischel, 1999). In this framework, self-control is defined as the extent to which the cognitive system obstructs the emotional system in driving behavioral decisions (Metcalfe & Mischel, 1999).

The balance between the cognitive and affective systems, or one's ability to exert self-control, is dependent on several factors (Connell, 2015; Rodriguez et al., 1989; Metcalfe & Mischel, 1999). The emotional system is dominant earlier in life, and as a person's prefrontal cortex develops with age, the cognitive system impacts decision making more often. The role of the cognitive system in goal-oriented decision making is partially related to temporal discounting. An augmented ability to reject immediate gratification in favor of a long-term goal is associated with several cognitive functions. The implementation of adaptive attention deployment strategies during a delay period, an understanding of the delay parameters, and intelligence jointly predict a person's ability to exert self-control by withholding actions that are in favor of short-term goals (Rodriguez, Mischel, & Shoda, 1989). In addition to age-related and temporal discounting-related differences in the balance between cognitive and affective systems, stress level plays a role as well (Metcalfe & Mischel, 1999). The cognitive system is more likely

to dominate goal-directed decision making in times of low or moderate stress and the influence of the emotional system increases as stress increases. The cognitive system would be most helpful in guiding decision-making during times of high stress, lending itself to an ironic situation in which self-control is most needed in times when it is the most difficult to access (Connell, 2015; Metcalfe & Mischel, 1999; Mischel & Ayduk, 2011).

The CAPS theory details how factors that influence the interaction between cognitive and affective abilities affect a person's capacity to exert self-control. Here, self-control is defined as the ability to withhold acting on emotionally charged or immediate desires by implementing cognitive impulse control strategies. The balance between the two systems, and the exertion of self-control, is impacted by age, stress, and cognitive ability. Understanding these mitigating circumstances allows for a more complete picture of how and why self-control failures occur and how they manifest in depression.

Common Themes Across Self-control Theories

There are common themes across these theories that illuminate how the many features of self-control are connected with one another. Each theory aims to explain how a person chooses a behavior and how they regulate their behavior during goal pursuit. Furthermore, each of the three recognizes the conflict between long-term goals and immediate desires, and that self-control encompasses the ability to suppress the latter to achieve the former. A core definition of the construct for the purposes of this study emerges from pulling together the central ideas from each theory: self-control is the cognitive ability to inhibit automatic behavior in the presence of multiple goals. All three of the theories described here call attention to the importance of cognitive function in sustaining goal-directed behavior. In Control Theory, attention and awareness are needed to recognize that a discrepancy exists between a person's current state and

desired state, which triggers the resolve of such discrepancy via self-control mechanisms. The CAPS theory similarly notes the importance of attention and awareness when faced with a choice between long-term and short-term goals. The Limited Resource Model suggests that effortful control of behavior via problem solving and other executive functions is needed to maintain long-term goals. Overall, cognitive functions are critical to successfully inhibit immediate temptations and desires.

The three theories acknowledge that these cognitive abilities serve to override a more automatic decision-making process that is often emotionally charged, reflexive, or immediately gratifying. The CAPS theory most explicitly details the relationship between the cognitive and affective components of self-control. In this context, the affective system is more inhibited in times of low stress and is less inhibited in times of high stress. This premise has been demonstrated in research studies that examined health-related decision-making abilities at various levels of stress. For example, exercise levels and effort to exercise decreased when individuals were stressed, even when it is in times of high stress that exercise is especially beneficial (Connell, 2015; Stetson et al., 1997). This finding indicates that it is more difficult to maintain long-term health goals when extensive emotional disturbances are present. Equally, according to the Limited Resource Model, trying to maintain long-term goals may contribute to emotional disturbances. This model states that self-control is a limited resource and exerting control in one domain impedes one's ability to regulate themselves in other domains. The core principle of ego depletion can be connected back to the effect of stress on self-control outlined in the CAPS theory. In times of high stress, a person could be putting forth effort to achieve emotional regulation, which could impede their ability to exert self-control in other domains. In turn, less impulse control strategies are available, which supports automatic and uncontrolled

behavioral choices. A shared premise across the three theories is that the ability to regulate goal-directed behavior is a balancing act between environmental demands and the strength of internal resources. Insight into how the cognitive and affective components of self-control operate to contribute towards goal-oriented behavior in neurotypical individuals allows clinical researchers to recognize, quantify, diagnose, and remedy self-control failures that are commonly present in psychopathologies.

Self-control and Psychopathology

A low level of self-control is implicated in a wide-ranging array of psychological dysfunction. People with low self-control are more likely to engage in high-risk behaviors such as reckless driving, domestic abuse, pathological gambling, and substance abuse (Chamorro et al., 2012; Potenza & de Wit, 2010). Low self-control in childhood and adolescence is indicative of poorer psychological health and subjective well-being in adulthood. For instance, Moffitt and colleagues (2012) found that compared to children in early developmental periods with greater self-control capacities, those with diminished self-control capacities had greater emotional distress and committed more crimes as adults. Self-control deficits are a prominent feature across groups of psychological disorders classified by higher-order factors of internalizing, externalizing, and thought disorders. Internalizing syndromes include depression, persistent depression disorder, general anxiety, panic disorders, and phobias, and externalizing syndromes include alcohol/drug dependence, antisocial personality disorder (ASPD), attention deficit hyperactivity disorder (ADHD), oppositional defiant disorder (ODD), and conduct disorder (CD) (Krueger, 1999). Poor self-control is evident in syndromes across these classifications (Santens et al., 2020). Indeed, these psychopathologies represent a growing public health concern due to

their high prevalence and subsequent societal costs that contribute to poor health and premature death (Schroeder, 2007).

The presence of low self-control in this broad range of disorders suggests that self-control may be a non-pathogonomic sign of psychopathology (Beauchaine & Thayer, 2015). Pathognomic models posit that the presence of certain symptoms is consistently indicative of a specific psychological disorder and that they share a common etiology. For example, if an individual presented with symptoms X, Y, and Z, they would be consistently diagnosed with a syndrome thought to be exclusively characterized by those impairments. The Diagnostic and Statistical Manual of Mental Disorders (DSM-5; American Psychiatric Association, 2013) is an example of a classification system that depends on pathognomic models (Beauchaine & Thayer, 2015). An alternative to this system is non-pathognomic models, which suggest that psychological disorders that appear to present as a single diagnosis at the behavioral level may arise from multiple different etiological pathways. These models adopt a dimensional approach, such that specific psychopathological syndromes are the result of differing levels of functional interactions between multiple neurobehavioral systems (Beauchaine & Thayer, 2015).

Beauchaine and Thayer (2015) put forth a non-pathognomic model of vulnerability to externalizing and internalizing disorders that theorizes that individual differences in underlying motivational systems interact with self-control to affect behavior. Underlying motivational systems are important to consider to better understand the etiology of psychological disorders. These networks are implicated in the expression of personality traits that play a primary role in decision making and information processing. Dimensional trait approaches such as Gray's motivational theory (Gray, 1982, 1987) describe the physiological bases of personality and its subsequent relationship with psychopathology (Beauchaine & Thayer, 2015). Gray theorized that

separate motivational systems exist that affect responses to environmental stimuli and determine behavioral outcomes. The behavioral activation system (BAS) is a network mediated by the mesolimbic dopamine pathway (i.e., ventral tegmental area, nucleus accumbens, ventral striatum) that encompasses appetitive motivational behaviors. The BAS is associated with approach toward reward, active avoidance of punishment, and pleasure that comes from reward seeking and attainment. The behavioral inhibition system (BIS) is a network mediated by the septo-hippocampal system (i.e., serotonin projections of the raphe nuclei and noradrenaline projections of the locus coeruleus) that encompasses aversive motivational behaviors such as passive avoidance of threat. The BIS is theorized to be the neural substrate of trait anxiety, and activation of this system induces feelings of anxiety.

The BIS/BAS motivational networks may serve as etiological substrates to increased vulnerability to externalizing and internalizing disorders. The higher vulnerability to these disorders coupled with poor self-control is theorized by some to be the pathway to psychopathology (Beauchaine & Thayer, 2015). This conceptualization pairs with the notions put forth in the leading theories of self-control that suggest that cognitive abilities serve to override a more automatic decision-making process that is often emotionally charged, reflexive, or immediately gratifying. Several studies have put forth that mesolimbic dopamine dysregulation (i.e., neural basis of BAS) is associated with a variety of traits associated with both internalizing and externalizing disorders (Beauchaine, 2001; Beauchaine & McNulty, 2013). As examples, 1) decreased mesolimbic and mesocortical reactivity to incentives is present in those with ADHD, CD, ASPD, and substance use disorders, 2) there are decreased volumes of mesolimbic dopamine transporters, D2 receptors, and D3 receptor binding in those with ADHD and alcohol use disorders, and 3) there is decreased functional connectivity between mesolimbic

and mesocortical structures associated with ADHD and CD during incentive responding. These findings suggest that abnormally high BAS is rooted in under-responsive mesolimbic dopamine functioning, which gives rise to trait impulsivity and leads to a vulnerability for externalizing behavior.

Individual differences in mesolimbic dopamine are not only associated with trait impulsivity, but also with positive affectivity. The latter association comes from reports that low levels of striatal dopamine are associated with trait irritability, and externalizing disorders such as ADHD, ODD, and CD are partially characterized by higher levels of irritability and negative affect. Collectively, these findings suggest that low mesolimbic dopamine may be the pathophysiological basis of externalizing disorders. Low levels of tonic mesolimbic dopamine result in irritable mood states, impaired reward processing, and behavioral impulsivity (Laakso et al., 2003). When experiencing negative emotions, individuals with this composition are more inclined to escape or relieve their state with impulsive reward and sensation seeking behavior compared to those with typical levels of mesolimbic dopamine. Due to impaired reward processing, the effect of this reward and sensation-seeking behavior is transient and motivates the individual to engage in increasingly high risks to obtain their desired state. This chain of reactions results in hyperactivity, impulsivity, and a vulnerability to externalizing psychopathology.

Low mesolimbic dopamine is considered by some to be a transdiagnostic substrate of both externalizing and internalizing disorders as this deficiency is not only associated with trait impulsivity, but also with depression. As discussed in the above paragraph, a lower striatal response to incentives is associated with less positive affect and maladaptive reward processing, both of which are characteristic symptoms of depression. Low mesolimbic dopamine has been

associated with additional symptoms of depression such as anhedonia and avolition. In this way, mesolimbic dopamine dysregulation may relate to an increased risk for internalizing and externalizing comorbidity as both positive affect and hedonic capacity are negatively affected. Sauder and colleagues (2012), for instance, reported that interactions between externalizing and internalizing symptoms accounted for a greater reduction in gray matter densities in mesolimbic regions than in either disorder cluster alone.

The interaction between BIS and BAS is critical to understand differences between internalizing and externalizing vulnerability. Previous studies have put forth that people with externalizing symptomologies tend to have lower trait anxiety than those without these symptoms (Corr & McNaughton, 2015). BIS, via the septo-hippocampal network, is considered the neural substrate of trait anxiety, and high BIS is associated with a vulnerability to depression but not trait impulsivity (Neuhaus & Beauchaine, 2013). Thus, individual differences in BIS may impact whether a person presents with externalizing or internalizing symptoms. Studies have suggested that trait anxiety may serve as a protective factor for people with dopamine system dysregulation who may otherwise be vulnerable to externalizing psychopathologies. The manifestation of psychopathy is an example of the complex relationship between the two motivational systems. Psychopathy has been associated with a deficient septo-hippocampal system, i.e., low BIS. These individuals have a functional reward valuation system but an under-responsive avoidance system; thus, they are less likely to experience anxiety with punishment and extinction cues. Accordingly, they would be less likely to experience punishment as an aversive outcome of their behavior and may feel more comfortable taking risks when either punishment or reward outcomes are possible (Beauchaine & Thayer, 2015).

The interactive effects of BIS and BAS on behavioral presentation highlights how the two corresponding neurobiological systems must be considered in tandem when differentiating between trait impulsivity and depression. Mesolimbic dopamine dysregulation and associated traits appear to increase an individual's vulnerability to externalizing disorders unless coupled with septo-hippocampal-mediated trait anxiety. Beauchaine and Thayer (2015) discussed a multidimensional conceptualization of psychopathology that takes these interactions into account. In their model, high BAS coupled with high BIS equates to a higher vulnerability to internalizing disorders, and high BAS coupled with low BIS corresponds to a higher vulnerability to externalizing disorders. The importance of individual differences in the relative strength of incentive processing systems and their effects on symptom presentation suggest these underlying dimensions aids in our understanding of the etiology of psychopathology rather than examining symptom presentation alone.

The dimensional trait model discussed above is a primary component of the manifestation of psychopathology, but the influence of top-down control of subcortical networks via the prefrontal cortex (PFC) may determine whether a person with externalizing or internalizing vulnerabilities exhibits impairment or not. Previous studies have indicated that trait impulsivity and trait anxiety are significantly more functionally impairing with co-occurring PFC dysfunction, as the PFC is associated with regulatory functions including self-control. Beauchaine and Thayer (2015) suggest that in the absence of PFC dysfunction, individual differences in trait impulsivity and trait anxiety would be more likely to simply manifest as personality characteristics rather than as psychopathological syndromes. To summarize the relationship between self-control and psychopathology according to Beauchaine and Thayer's (2015) model of vulnerability, individual differences in underlying motivational systems interact

with self-control to affect behavior across psychopathological disorders. A general vulnerability to psychopathology appears to be determined by PFC dysfunction, and specific vulnerabilities to externalizing, internalizing, or both categories of symptom clusters may be better determined by considering the functional nature of top-down cortical networks.

Despite the extent of self-control impairment across syndromes, the exact role that self-control plays in the etiology of disorders has yet to be fully explored, including its role in emotional disorders specifically (Coyne & Gotlib, 1983; Strauman, 1992). This study will focus specifically on the relationship between self-control and depression. It is unknown if multiple pathways exist that lead to the development of self-control difficulties, or if early biological difficulties with self-control predisposes an individual to the incidence of later behavioral difficulties and poor symptom management (Strauman, 1992). Examining the physiological and behavioral correlates of poor self-control can aid in the understanding of how the construct is connected to psychopathologies characterized by emotional dysregulation, specifically depression.

Self-control and Depression

The relationship between cognitive processes and emotional regulation put forth from theories of self-control suggest that poor self-control is implicated in the etiology of depression. Clinical depression is a mood disorder characterized by episodes of symptom clusters that negatively affect how an individual feels, thinks, and carries out daily activities (National Institute of Mental Health, 2018). Those with depression experience cognitive, affective, and somatic symptoms. For a diagnosis of clinical depression according to the DSM-5, individuals must have experienced a depressed mood or loss of interest in daily activities in addition to several other symptoms for a period of at least two weeks (National Institute of Mental Health,

2018). The severity, frequency, and quantity of symptoms vary on an individual basis, but may also include the following: feelings of hopelessness, worthlessness, guilt, helplessness, or restlessness; irritability; lethargic movements or speech; difficulties with concentration, memory, or decision making; sleep disturbances; appetite or weight changes; thoughts of death or suicide; or suicide attempts (National Institute of Mental Health, 2018).

Gaining a better understanding of depression is critical due to the high prevalence of depressive episodes in the general population. According to the National Institute of Mental Health (2019), 17.3 million adults (7.1% of all adults) in the United States reported at least one depressive episode in 2017, and 63.8% of those adults reported severe impairment. Furthermore, 264 million people endure depression globally and is a leading cause of disability worldwide (World Health Organization, 2020). The development of depression results from a complex interaction of psychological, social, and biological factors, the latter of which include stress and cardiovascular disease (World Health Organization, 2020). The highly variable symptom presentation of depression and the multifaced contributing factors indicate a need to identify how these dynamics interact to disrupt cognitive and emotional regulation.

The precise role of specific cognitive functions, namely self-control, in the etiology of depression, has yet to be fully understood. However, researchers have put forth theories that frame depression as a disorder of regulatory processes. One such theory posits that depression is a consequence of failed goal pursuit (Hoyle & Gallagher, 2015). There are several processes involved in the initiation and management of goal pursuit that must transpire to successfully attain a goal or desire. Once the pursuit of a goal is initiated via opportunity, motivation, and sufficient cognitive resources, regulatory processes must act to persist in the pursuit of reward, maintain interest, and monitor effectiveness. Successful goal pursuit occasionally calls for

disengagement or substitution if the goal is no longer relevant or attainable (Strauman, 2017). Difficulties in any of these steps, including initiation, maintenance, management, resolution, and disengagement, are prominent features in depression along with several other psychological disorders (Ruscio et al., 2011; Strauman, 2017). In particular, the failure to disengage from unsuccessful or irrelevant goal attainment attempts is attributed to perseverative tendencies that characterize depression, including worry, rumination, and brooding (Koster et al., 2011). Self-control abilities enable a person to choose appropriate actions that promote goal attainment and suppress actions that do not serve the person's goals. If a person has poor self-control capacities, it stands to reason that they may experience these difficulties associated with depression due to an inability to shift away from goal pursuits that no longer serve them.

A second model by Brinkman and Franzen (2015) suggests that individuals with depression put forth a maladaptive intensity of effort in pursuit of their goals that produce difficulties commonly manifested in the syndrome. Intensity of effort refers to the vigor and engagement individuals yield to achieve their goals. In a healthy system, the effort that is given towards a goal is proportional to achievement difficulty as long as the attainment of the goal is possible and justified (Brehm & Self, 1989). As the attainment of the goal increases in difficulty, the more effort people will deliver. Furthermore, when the goal becomes impossible to achieve or when the difficulty surpasses the value of success, people will withhold effort. When the difficulty of the goal or standard for success is unknown, people will depend on goal importance to determine how much effort to put forth: more effort will be expended as importance increases (Brehm & Self, 1989). The importance of self-control is illustrated here, as the ability to purport an appropriate amount of effort towards attaining a goal and knowing when to inhibit responses that are no longer beneficial are hallmarks of the construct.

Brinkman and Franzen (2015) linked the persistent negative affect prevalent in depression with maladaptive goal pursuit intensities. In the mood-behavior model, mood states have indirect effects on appraisals of our environment, which affects behavioral choices (Gendolla, 2000). In situations where individuals with depression engage in goal-related tasks, Brinkman and Franzen (2015) found that those with a depressed mood perceived a cognitive task to be more difficult. This chain of events leads to higher effort put forth for easier tasks, but disengagement for more difficult but still attainable task goals. The authors concluded that the perceived standard of success and cognitive demand it would take to achieve the difficult but attainable goals contributed to the disengagement.

Further research has linked a maladaptive intensity of effort in goal-related decision making to difficulties that are commonly observed in depression. Individuals with depression often set higher standards for themselves than are realistically attainable and struggle with initiating actions and task strategies (Brinkman & Franzen, 2015). Additionally, people with depression demonstrate maladaptive responsiveness to negative feedback and poor attentional disengagement from negative events (Koster et al., 2011). Together, these facets relate to a ruminative self-focus, difficulties in emotional regulation, and perseverance of negative mood states (Aldao et al., 2010; Joormann & Siemer, 2011). This model and the theory proposed by Hoyle and Gallagher (2015) reveal clear links between self-control and depression in the context of goal-pursuit. Poor self-control is associated with an inability to shift away from irrelevant or unimportant goals and a tendency to exert an inappropriate amount of effort towards achievement that is disproportional to goal characteristics. These cognitive errors may drive difficulties commonly exhibited by individuals with depression, such as perseverative behavior, goal disengagement, and poor task switching. Due to the stark association between self-control

and depression, as well with as many other psychopathologies, clinical researchers have constructed measurements to assess self-control to predict, understand, diagnose, and treat indices of dysfunction.

Measurement of Self-control

There is a wide variety of measures available to researchers to assess self-control. The choice of methodology is often one of the greatest challenges when seeking to examine the construct. Behavioral, self-report, and neuroscientific methods exist for researchers to choose from, but there are limitations to each.

Self-report Questionnaires

A meta-analysis has identified that there are over 100 different self-report questionnaires that measure self-control (Duckworth & Kern, 2011). These types of assessments of self-control are the most commonly used and have been shown to predict academic achievement, health, criminal activity, drug use, and more (Duckworth et al., 2010; Moffitt et al., 2011). Scale items demonstrate high heterogeneity across measures, and many conceptualize self-control as the inverse of impulsivity (Duckworth & Kern, 2011). These measurement characteristics are problematic in a number of ways. Defining self-control as the inverse of impulsivity may be assessing a different piece of the construct than others that define self-control and impulsivity as separate processes. Furthermore, the heterogeneity across measures indicates that each self-report scale may be tapping into different components of self-control regardless of its defined relationship with impulsivity. This concern has been validated in analyses that reported that the choice of measure across studies accounted for 53% of the variation in effect size (Duckworth & Kern, 2011). These difficulties expound the complexity of self-control and suggest that a self-report measure that fully captures the construct may still be an unachieved milestone in the field.

Researchers would do well to identify which components of self-control are most critical to their research question when choosing a measure to include in their studies.

Behavioral Tasks

Behavioral tasks that aim to capture self-control can be broken into two main categories: those that assess the executive function components of self-control and those that assess temporal discounting (Duckworth & Kern, 2011). Executive function is defined as a set of goal-directed cognitive abilities in which top-down, high-level control is exerted over bottom-up, low-level processes (Williams & Thayer, 2009). Executive function is a multidimensional construct that encompasses various aspects of complex cognitive operations, such as working memory, response inhibition, task switching, and attention (Miller, 2000; Miyake et al., 2000). The executive function components of self-control pertain to the abilities to inhibit inappropriate responses, maintain multiple goals at once, and incorporate feedback into continued behavioral choices. Meanwhile, behavioral tasks that assess temporal discounting components of self-control capture abilities related to achieving a delay of gratification such as attention strategies and comprehension of task instructions (Duckworth & Seligman, 2005; Mischel et al.,1989; Newman et al., 1992).

Several limitations exist among behavioral tasks that assess self-control. One critique is that executive functioning tasks tap into multiple aspects of cognition without successfully isolating self-control-related processes. Indeed, a meta-analysis determined that there was a lack of convergent validity of executive function tasks, both within this category and when compared with others (Duckworth & Kern, 2011). Temporal discounting tasks were more homogenous than executive functioning tasks in the same meta-analysis, but the authors acknowledge that this finding could be attributed to the relative paucity of temporal discounting studies compared to

executive function studies (Duckworth & Kern, 2011). Even if the homogeneity of temporal discounting tasks is indeed more valid, these tasks do not capture aspects of self-control that are distinct from temporal discounting. As with self-report measures, it may be prudent to consider the specific features of self-control that are presumed to be pertinent to the research question at hand when choosing a behavioral task. A compromise may be to select multiple tasks and self-report measures when designing studies that aim to assess self-control. However, the correlation between self-report measures and behavioral tasks of self-control is weak and lacks reliability (Duckworth & Kern, 2011; Meyer, 2001). This challenge has been met with efforts to identify biomarkers of self-control through neuroscientific methodology to use in conjunction with other types of measures.

Neuroscientific Biomarkers

Biomarkers are defined as biological attributes that can be measured to evaluate health-related constructs (Naylor, 2003). They provide an objective way to characterize dysfunction, and by finding biomarkers, researchers can better predict, diagnose, and monitor signs of impairment (Mayeux, 2004). Investigations that have aimed to identify biomarkers of self-control have traditionally employed task-based neuroscientific methods such as EEG and fMRI.

Neuroimaging studies have expanded our knowledge of the neural correlates underlying goal-directed decision-making and self-control (Hofmann, 2015). Self-control supports the capacity to evaluate the constituents of a situation to appropriately react and respond. Individuals commonly utilize this ability in emotional contexts to regulate their responses. When a person is confronted with a potentially emotionally arousing stimulus in the environment, self-control capacities urge the person to consider mitigating circumstances or reappraise the situation, such

as assigning meaning to ambiguous cues, assuming plausible implications, and employing strategies to adjust emotional value before reacting (Morawetz et al., 2017).

Several fMRI studies support the role of self-control in reappraisal and emotional regulation. A widespread network of brain regions is implicated in this relationship. The prefrontal cortex (PFC) is extensively associated with self-control abilities, including the dorsolateral and dorsomedial PFC (dlPFC and dmPFC), ventrolateral and ventromedial PFC (vlPFC and vmPFC), inferior frontal gyrus (IFG), and orbitofrontal cortex (obPFC). Temporal regions involve the temporal pole, superior temporal gyrus (STG), and temporo-parietal junction (TPJ). Additional regions associated with the construct of self-control include inferior parietal regions, anterior cingulate cortex (ACC), insula, striatum, and amygdala (Buhle et al., 2014; Kohn et al., 2014; Ochsner et al., 2012).

Furthermore, neuroimaging studies indicate a critical role of the connection between the amygdala and PFC regions in emotional regulation via self-control. Greater rates of reappraisal of emotional stimuli are associated with decreased activity in the amygdala and increased activity in the dlPFC, dmPFC, and lateral obPFC (Drabant et al., 2009). Reappraisal has been linked to amygdala and vlPFC activity as well as to amygdala-PFC functional connectivity (Eippert et al., 2007; Lee et al., 2012). These results indicate that self-control is reliant on higher-order cognitive regulation from the PFC to modulate and adjust automatic, emotional reactions to stimuli from the amygdala.

Studying the biomarkers of self-control is beneficial for supporting and expanding upon theory-driven research. One of the most widely accepted conceptualizations of self-control is that the ability aligns with dual-process models, in which a “reflective” system that values long-term goals suppresses an “impulsive” system that prioritizes short-term gains (Heatherton & Wagner,

2011; Hofmann et al., 2009). Kronke and colleagues (2020) have put forth evidence supporting a complementary theory using fMRI results. This theory posits that self-control depends on the dynamic interaction between neural value representations and anticipated future outcomes of behavioral choices (Berkman et al., 2017). The subjective value of each choice is calculated by considering the associated short- and long-term gains and costs. Kronke and colleagues (2020) hypothesized that self-control is associated with the ability to anticipate long-term consequences in the decision-making process and to incorporate those calculations when assigning value to behavioral choices. The authors found that activity in the vmPFC was positively associated with the subjective value of goal-directed behaviors and that activity was modulated by anticipated long-term consequences. This relationship was, in turn, predictive of self-control failures in a goal-related behavioral task, such that less anticipation of these consequences was correlated with more self-control failures. Overall, these findings correspond with previous research that suggests the vmPFC is implicated in reward processing, determining the subjective value of behavioral reinforcers, and considering the affective components of imagined future consequences (Bartra et al., 2013; Benoit et al., 2014; Bray et al., 2010).

These fMRI studies demonstrate that a wide array of neuroanatomical structures and networks are associated with self-control. Research that utilizes EEG methodology provides additional information that supplements our understanding of the construct. As described in the above text, biomarkers of self-control have been associated with the ability to reappraise emotionally arousing situations and incorporate long-term consequences into the value of behavioral choices. Moreover, Kronke and colleagues (2020) provided support for the hypothesis that self-control is not simply a suppression of short-term values from overriding long-term goals

but is an interaction between the determined subjective value of a response and anticipated future outcomes.

A source localized event-related potential (ERP) study conducted by Harris, Hare, and Rangel (2013) reported findings that suggest that both conceptualizations of self-control better characterize the construct than either one on its own. The study tested the two models by considering the purported functions of the dlPFC and vmPFC in self-control-related functions. Research has suggested that the vmPFC encodes stimulus values that direct decisions when a choice is being made, and that the dlPFC modulates these values to reflect the long-term goals (Baumgartner et al., 2011). This relationship supports the theory described by Kronke and colleagues (2020) that value adjustment interacts with anticipated outcomes to characterize self-control. Conversely, further research has suggested a slightly different role of these PFC areas that corresponds to the other model of self-control, in which a long-term valuation system overrides impulsive, short-term desires. These studies frame the dlPFC in the context of an attentional network that modulates early sensory responses (Yamaskai et al., 2002). This dlPFC function, termed attentional filtering, suppresses responses by reducing the processing of distracting, goal-irrelevant information (Harris et al., 2013).

ERP methodology has an advantage over fMRI in determining which model is more accurate due to the high temporal resolution of EEG. If self-control reflects attentional filtering, then ERPs associated with early perceptual processing should differentiate between self-control failures and successes in a behavioral task. If self-control reflects value modulation, there should be differences in EEG indices with later latencies that are more associated with these cognitive functions (Harris et al., 2013). The authors of the source localized ERP study found that both conjectures were true. Individuals with better self-control were defined both by ERP responses

early in the decision-making period (N1 amplitudes 150-200 milliseconds post-stimulus), and EEG changes at later latencies (alpha bandwidth 450-650 milliseconds post-stimulus). Furthermore, source localization of these EEG components indicates that the dlPFC plays a role in both early suppression of potential distractors and in the modulation of vmPFC activity at later latencies (Harris et al., 2013).

ERP methodologies have broadened our understanding of the role that the ACC plays in self-control. The ACC is implicated in goal-directed cognitive processes including self-monitoring and the regulation of behavioral choices (Bush et al., 2000). The event-related negativity (ERN) ERP is thought to be generated by the ACC and reflects electrophysiological activity associated with the commission of behavioral errors (Dehaene et al., 1994). Increased ERN amplitudes have been reported following errors on behavioral tasks when the actual outcome does not match the expected outcome of a decision. As such, the ERN is considered an index of conflict monitoring that alerts the person when a miscalculation occurred in the decision-making process (van Veen & Carter, 2002). This ability to compare actual to expected results of a behavioral choice enables the person to learn from their mistakes and consider the consequences of their choices for future decision making. The outcomes of this study, along with those previously discussed, expand the field's understanding of biomarkers of self-control and promote the utility of using biomarkers to understand how the multifaceted components of self-control contribute to maladaptive behavioral outcomes. With that said, limitations to these methodologies should not be disregarded and the exploration of novel biomarkers of self-control may be beneficial.

As with self-report questionnaires and behavioral tasks, there are drawbacks to assessing self-control with fMRI and EEG methods. Both EEG and MRI equipment, training, and analysis

tools are expensive, which may limit the practicality of the methods in laboratory settings. Furthermore, these neuroscientific methodologies rely upon behavioral tasks to evoke self-control-related processes in order to correlate differences in performance to neuroanatomical structures. The high heterogeneity of these behavioral tasks calls into question the validity of claims that correlate performance with fMRI and EEG variations. Many of the tasks either measure one component of self-control (i.e., temporal discounting tasks) or fail to isolate self-control from other cognitive functions (i.e., executive functioning tasks). The ability of fMRI and EEG to accurately identify self-control processes is in part limited by the construct validity of behavioral tasks. In this light, biomarkers of self-control that do not require task-based designs may prove to be advantageous to the field.

Investigations using EEG and fMRI, while imperfect, have undoubtedly progressed the field in gaining a deeper understanding of self-control. These studies have reported that several neural structures are implicated in self-control function that overlap with those associated with depression. The extensive range of neural correlates substantiates the difficulties in defining and measuring the construct. Findings widely support the notion that self-control is not a function isolated to a single brain area and may best be conceptualized with a network approach. A biomarker measurement that reflects the various regions associated with self-control, including PFC regions, ACC, amygdala, and others in a single integrated network is worthwhile to consider.

Heart Rate Variability

The following section contends the potential of a cardiovascular measurement, heart rate variability, as a biomarker of self-control. Heart rate indices have been traditionally employed in psychophysiological studies as increased heart rate is associated with heightened emotional

arousal and with the body's response to stress (Young & Benton, 2018). More recently, researchers have discovered that the time interval between beats varies according to several internal and external factors and is considered an index of a person's ability to regulate responses to environmental demands (Jarczok et al., 2015; Young & Benton, 2018). The irregularity in time intervals between successive heartbeats is referred to as heart rate variability (HRV). High HRV refers to frequent changes in the time between one heartbeat to the next, while low HRV is distinguished by less irregularity in the beat-to-beat rhythm (Shaffer et al., 2014).

HRV measurement is a powerful, non-invasive tool that reflects biophysical regulation. Many healthy biological systems are characterized by non-linear dynamics associated with mathematical chaos such that rhythms fluctuate spontaneously and inconsistently rather than in a fixed and stable pattern (RenuMadhavi & Ananth, 2012). This type of pattern reflects a person's ability to quickly adapt biological systems to moment-to-moment changes in the environment. A cardiovascular system capable of rapid fluctuations can be both malleable and highly responsive to complex demands (Thayer et al., 2012).

In this light, high HRV, or frequent variations in time between successive heartbeats, is indicative of an adaptive and flexible physiological system (Porges, 1996). Chronic low HRV is associated with poorer health and a decreased ability to flexibly cope with uncertainty and change in the environment (Shaffer & Ginsberg, 2017). Low HRV has been implicated in numerous types of psychological dysfunction, such as poor behavioral and cognitive functioning, behavioral inflexibility, depression, generalized anxiety disorder, post-traumatic stress disorder, emotional dysregulation, and poor inhibitory control (Appelhans & Luecken, 2006; Hansen et al., 2003; Kemp et al., 2012; Kluttig et al., 2010).

There is substantial evidence for the potential of HRV as a biomarker for self-control and associated psychological dysfunction. An understanding of healthy autonomic function is first needed to appreciate the derivations of HRV and how the measurement relates to neural structures that reflect self-control ability.

Autonomic Nervous System

The autonomic nervous system (ANS) is a branch of the peripheral nervous system that regulates the internal environment of the body along with the endocrine system. The endocrine system carries out regulatory functions using chemicals that make up hormones that allow for a slower, more diffuse control of target tissues. Conversely, in the ANS the primary mode of communication with the rest of the body is through electrical impulses. These electrical impulses specifically target structures for a finer, more discrete control of functioning. The ANS innervates exocrine glands, such as sweat glands, that then secrete products into ducts to carry out intended regulatory functions (Gabella, 2012; Janig, 1989).

Two branches of the ANS include the parasympathetic nervous system (PSNS) and sympathetic nervous system (SNS). Both branches intend to maintain stability of the internal environment. The SNS responds to sudden severe exercise, fear, or rage, and helps the body prepare for an emergency, while the PSNS conserves and restores energy in times when there is no threat detected. The SNS and PSNS are often harmonious in that the two branches regulate opposing functions. As examples, the SNS can dilate the pupil, relax bronchi to allow for more airflow, accelerate heart rate, and relax the bladder, while the PSNS can constrict the pupil, constrict bronchi, lower or inhibit heart rate, and constrict the bladder (Gabella, 2012; Janig, 1989). The SNS and PSNS work together to create an internal environment that adapts to the ever-changing demands of the external environment.

Neurons of the SNS utilize acetylcholine (ACh) for presynaptic communication and produce norepinephrine (NE) and epinephrine (EPI) for postsynaptic communication with target tissues (Sternini, 1997). These target tissues primarily center upon regulation of blood vessels, especially in the presence of threats, to appropriately react to environmental stressors (Waxenbaum et al., 2020). SNS signals cause coronary vessels, and vessels that supply skeletal muscles and external genitalia, to dilate (i.e., vasodilation) and all other vessels to constrict (i.e., vasoconstriction). SNS-related cardiac function is compromised in pathological states such as coronary artery disease. Here, coronary arteries may constrict with SNS output and detrimentally increase metabolic demand (Vargas Pelaez et al., 2016). The SNS is perpetually active, even in non-stressful times. Additional functions that are routinely performed include the dilation of airways and the regulation of inflammation during an immune response (Elenkov et al., 2000; Karemaker, 2017).

The PSNS utilizes ACh for both pre- and post-synaptic communication (Waxenbaum et al., 2020). 75% of the PSNS is comprised of the vagus nerve, which is the tenth cranial nerve and has cell bodies located in several nuclei within the medulla oblongata (Karemaker, 2017). The vagus nerve provides PSNS input to most thoracic and abdominal viscera, including motor innervation of the heart, and communicates sensory information from baroreceptors of the carotid sinus and aortic arch. Cardiovascular regulatory functions of the vagus nerve promote relaxation by reducing contractility of the atria and ventricles and by reducing conduction speeds (Waxenbaum et al., 2020). These operations work in concert with complex dynamics intrinsic to the heart to regulate autonomic performance.

Cardiovascular Function

There is a complex system of neurons within the heart termed the intrinsic cardiac nervous system that functions with the ANS to regulate cardiac function (Kukanova & Mravec, 2006; Verkerk et al., 2012). Autorhythmic cells within the heart spontaneously generate action potentials that produce contractions of cardiac muscles (Waxenbaum et al., 2020). Bundles of these autorhythmic cells function as "pacemakers" to initiate the heartbeat. Two such pacemakers are the sinoatrial (SA) node and the atrioventricular (AV) node. The movement of the electrical impulse from these nodes to the rest of the heart to initiate myocardium (i.e., cardiac muscle) contraction is recorded via an electrocardiogram (ECG). Each peak and trough of the ECG signal represents a distinct point in this process, and each repetitive segment of the ECG is considered one cardiac cycle (Waxenbaum et al., 2020). The cardiac cycle is initiated at the SA node, where autorhythmic fibers spontaneously depolarize at a rate of 60-100 action potentials per minute. The impulse then travels to the AV node through the atria. The myocardium of the atria depolarize as the signal is transmitted and results in atrial contraction. The moment that the atria contracts is the "P" wave, or first peak, of the ECG. From the AV node, the electrical impulse is transmitted from the top of the septum to the bottom, then to the myocardial fibers of the ventricles. The depolarization of ventricular muscle fibers produces the "QRS" complex of the ECG, where the "R" wave is the second peak in the cycle. The interval between the "P" and "R" waves represents the time it takes for the electrical impulse generated in the SA node to reach the ventricles. After the depolarization of the neurons within the ventricle, the cells repolarize, and the ventricle muscles relax. The repolarization of these ventricular cells is reflected by the "T" and "U" peaks in the ECG. This final effort is considered the end of one cardiac cycle and the process repeats (Waxenbaum et al., 2020). The peaks and

troughs of the ECG during cardiac cycles are important to be familiar with as they are utilized in the quantification of HRV. Overall, this progression illustrates that the interaction between the PSNS, the SNS, and the intrinsic cardiac nervous system generates and regulates the fluctuating pattern of the heart rhythm.

ANS Regulation of the Heart

Both the PSNS and SNS innervate fibers of the intrinsic cardiac nervous system to adjust the heart rate according to changing environmental demands. In a healthy system, the heart rate will be higher when facing challenges, completing tasks, or in the presence of stressors, and will be lower in the absence of those conditions or during sleep. The body is constantly processing information to check that the heart rate is appropriate for the context.

While both branches of the ANS are continuously active, the PSNS is dominant during periods of rest. Vagus nerve fibers project to the SA and AV nodes within the intrinsic cardiac nervous system. Stimulation of these pacemakers from vagal input inhibits the rate of spontaneous depolarization and causes the release of ACh to bind to muscarinic receptors to affect cardiac muscle (Waxenbaum et al., 2020). The intrinsic heart rate generated by autorhythmic cells of the SA node is 107 beats per minute (BPM) and steadily decreases with age (Opthof, 2000). An average resting heart rate with vagal nerve input is 75 BPM, although the PSNS can slow the heart rate to 20-30 BPM or even stop the heartbeat altogether (Tortora & Derrickson, 2014).

SNS nerves target the SA and AV nodes of the intrinsic cardiac nervous system to increase the heart rate. Following SNS input, action potentials conducted by motor neurons of the myocardium trigger the release of NE and EPI. These neurotransmitters bind to beta-adrenergic (β1) receptors on myocardial fibers. SNS activity increases the speed at which

depolarization occurs at the SA and AV nodes, which increases the contractility of the atria and thus increases heart rate (Waxenbaum et al., 2020). In deteriorating hearts, such as those associated with disease or advanced age, the number of β1 receptors declines and myocardial contraction in response to NE and EPI is reduced (Ogletree-Hughes et al., 2001).

Examining how the PSNS and the SNS exert separate influences on the heartbeat permits a better understanding of how the balance between the two branches affects HRV and offers insight into potential techniques to measure HRV. The heart rhythm is the net effect of PSNS and SNS influences on the intrinsic cardiac nervous system. These ANS branches do not only differ in the intended effect on heart rate and in how they produce the effect, but also in the time to onset and time the effect lasts. Changes to heart rhythms are quicker to take effect when stimulated by the PSNS but they last longer when stimulated by the SNS (Hainsworth, 1995). PSNS stimulation via the vagus nerve results in an immediate effect on the heart rate; the heart rate is slowed within one to two beats after the signal began. However, the heart rate quickly adjusts towards its previous state after stimulation ends. In this way, an increase in heart rate can either be attributed to the presence of SNS stimulation or the absence of PSNS stimulation. The effect of the SNS on the heart rate contrasts with the effect of the PSNS in that the former induces a change in heart rate five seconds after the signal began, and the change is sustained if there is continuous stimulation for 20 to 30 seconds. This substantial delay suggests that sudden changes in the beat-to-beat rhythm of the heart rate, corresponding to HRV, can be attributed to the vagus nerve through the PSNS, more so than the SNS (Hainsworth, 1995). The competing impulses from the SNS and PSNS on the SA node are implicated in the unpredictable and highly flexible rhythm of the heartbeat characterized by chaotic dynamics. This pattern is critical in permitting the body to quickly adapt to changing environmental demands.

Chaotic Dynamics of the Heart Rhythm

Scholars have often described the functions of the bodily systems as working towards the goal of maintaining homeostasis. According to the original definition put forth almost one hundred years ago, homeostasis describes the idea that physiological systems function to reduce variability in an effort to maintain a constant internal environment (Cannon, 1929). A healthy system was thought to be comprised of the ability to detect and correct a disturbance from baseline and to remain static in a resting state until disturbed again. As available scientific methods to observe physiological functions progressed, researchers began to question the accuracy of this idea. Electroencephalograms demonstrated the irregularity of brain wave patterns, serum assays provided evidence that hormone levels inconsistently fluctuate, and ECGs exhibited heart rhythm patterns that were not predictably regular (Goldberger, 1991). At this time, it appeared that irregular and somewhat unpredictable physiological variability was a sign of health and not disease or dysfunction. Further studies then indicated that the notion that complexity was always better was not always the case, either. Vaillancourt and Newell (2002) showed that in certain systems, a decrease in complexity was indicative of declining health, while in other systems the opposite was true. Overall, these studies demonstrated that the idea that homeostasis is a universal goal of all physiological systems is too simplistic and inaccurate. Highly complex and inconsistent (i.e., chaotic) patterns within systems can be constructive.

Chaotic dynamics within biological systems such as heart rhythm regulation can be advantageous. The external environment constantly changes on a moment-to-moment basis; thus, the ability of the body, and specifically the heart, to quickly adapt to these changes is important for survival and is a sign of healthy functioning (Shaffer & Ginsberg, 2017). Chaotic systems

are, by definition, highly variable, and this plasticity fits the body's need to flexibly adapt to unpredictable demands (Goldberger, 1991).

In instances where a previously chaotic system becomes more predictable, or vice versa, difficulties in appropriately modifying physiological and behavioral responses to match situational context may ensue. Understanding the purpose of chaotic dynamics in healthy biological systems aids in identifying how breakdowns in these forces contribute to poor health outcomes. Voss and associates (2008) suggested three potential causes for chaotic behavior within biological systems and explanations for differing degrees of complexity across systems: 1) Various subsystems of a network with feedback mechanisms must constantly adjust to meet changing environmental demands, 2) A subsystem may need to adapt to take on the demands of the entire network in instances of pathophysiological dysfunction or as the body ages, and 3) Subsystems that cooperatively interact with each other may need to adapt to compensate for an entirely failed subsystem within the network following severe pathophysiology. In these instances, the interdependence and connectedness of multiple systems within a network that results in complexity aids in the regulation of bodily functions and provides a safety net in times of crisis.

The function of chaotic properties of the heart rhythm is supported by the first explanation put forth by Voss and associates (2008), that subsystems of a network with feedback mechanisms must constantly adjust to meet changing environmental demands. As previously mentioned, the SNS and PSNS exert their influence on the SA node of the intrinsic cardiac nervous system to alter the heart rate in accordance with feedback and situational contexts. The SA node concurrently receives competing stimulation from both the SNS and PSNS, and the resultant heart rate is determined by the net value of these forces. It is this constant tug of war

directed towards the SA node that is thought to be the mechanism that drives the chaotic variability of the heartbeat (Goldberger, 1991). The dynamic between these systems that stimulate the SA node to produce the variable heart rhythm can be quantified by measuring the time interval in between individual heartbeats, or inter-beat interval (IBI) (Voss et al., 2008). The IBI is often calculated using the "R" peaks within the QRS complexes of an ECG recording (Task Force, 1996).

The natural unpredictability of the exact rhythm of the heart is rooted in the complex effects of the SNS and PSNS on the intrinsic cardiac nervous system (Reyes Del Paso et al., 2013). These fluctuations in the IBI characterizes what is known as HRV. HRV is used as a proxy to assess neurocardiac functioning, as interactions between the heart and the brain act in conjunction with the ANS to produce the oscillatory patterns (Shaffer & Ginsberg, 2017). The chaotic properties are evident when comparing individual components of the heart rate on a beat-to-beat basis, such as with the variability of the IBI (Shaffer et al., 2014).

High HRV is associated with high variability between IBIs, in that the time intervals between individual cardiac cycles, or heartbeats, is highly variable from one to the next. Low HRV is associated with low variability between IBIs, in that the heart rhythm displays more predictability and less variability on a moment-to-moment basis. In general, chronic low HRV is associated with poorer health and a decreased ability to flexibly cope with uncertainty and changing situational demands (Shaffer & Ginsberg, 2017). The evidence of maladaptive functioning implies that the SNS and PSNS exertions on the heart rhythm are imbalanced in those with low HRV, and that this imbalance negatively affects chaotic dynamics that normally function to support healthy regulatory processes. These autonomic regulatory processes are interconnected with neural structures that are implicated in cognitive and emotional control as

well. The following subsection details the network that connects brain regions to autonomic structures that ultimately determine the heart rhythm. In doing so, the case builds for the utility of HRV as a biomarker for neural processes, including self-control.

Central Autonomic Network

The Central Autonomic Network (CAN; Benarroch, 1993) is a proposed system of direct and indirect bi-directional pathways that link the prefrontal cortex (PFC) to autonomic motor circuits. The model lays the groundwork for the notion that adaptive, goal-directed behavior is contingent on communication between central and autonomic components that regulate cardiovascular function. The CAN pathways are responsible for both excitatory effects on the heart via the SNS and inhibitory effects on the heart via the PSNS. In the other direction, communication from these autonomic and cardiac components back to cortical and subcortical structures affect neurological function. The full pathway starts on one end in the PFC. Following the appraisal of a stimulus, the obPFC and medial prefrontal cortex (mPFC) decrease the expression of the inhibitory neurotransmitter GABA in the central portion of the amygdala (CeA) (Thayer et al., 2012). As described in previous subsections, the connections between the amygdala and several PFC regions are importantly implicated in the ability of self-control processes to influence emotional regulation by reappraising emotionally arousing stimuli as needed. The CeA in particular is associated with the modulation of cardiovascular, autonomic, and endocrine responses to stress and threat (Thayer & Lane, 2000). These connections reveal that links between PFC and amygdala output can alter the functioning of other biological systems, and vice versa.

The disinhibition or activation of the CeA can produce changes in the heart rate in a number of different ways (Thayer et al., 2012). First, disinhibition of the CeA can lead to

disinhibition of the caudal ventrolateral medulla (CVLM), which leads to activation of sympathoexcitatory neurons in the rostral ventrolateral medulla (RVLM). The activation of these neurons causes an increase in SNS activity and an increase in heart rate. Second, disinhibition of the CeA could cause a decrease in PSNS activity to increase heart rate. In this case, disinhibition of the CeA leads to an inhibition of neurons in the nucleus of the solitary tract (NTS). This inhibition leads to the inhibition of the nucleus ambiguus and the dorsal vagal motor nucleus, which decreases PSNS. Less PSNS input causes an increase in heart rate. Lastly, disinhibition of the CeA can act directly to disinhibit sympathoexcitatory neurons in the RVLM to increase SNS activity and heart rate. However, this direct method to increase SNS is minor and uncommon (Thayer et al., 2012). This model demonstrates that fluctuations in the time intervals between heart beats, or HRV, is the result of a complex network that functionally connects neurocardiac structures. Importantly, interactions between PFC regions and subcortical regions, namely the amygdala, shape cardiac output patterns and vice versa. This relationship would give support for a theory that neurocognitive functions, namely self-control, that are associated with these structures are intimately related to heart rhythms and that heart patterns may serve as a proxy measurement for more abstract cognitive functions.

The CAN models a complex series of cortico-subcortical circuits that ultimately control changes in heart rhythms (Kemp & Quintata, 2013). The network is bidirectional in that feedforward and feedback loops link the brainstem with several forebrain structures, including the obPFC, mPFC, cingulate cortex, insula, amygdala, and the hypothalamus (Benarroch 1993; Shaffer et al., 2014). The different pathways within the CAN have the ability to either decrease heart rate via PSNS suppression or increase heart rate via SNS activation. The SNS and PSNS innervate the SA node of the heart via stellate ganglia or the vagus nerve, respectively (Thayer et

al., 2009). With less PSNS activity, less ACh is released at the SA node, which causes less inhibition of cardiac muscle and an increased heart rate. With more SNS activity, more NE is released at the SA node to excite cardiac muscle and increase heart rate (Kemp & Quintana, 2013). The continual contrasting influences of the PSNS and SNS are reflected in the highly variable dynamics of beat-to-beat changes in the heart rhythm, or HRV. These changes are purposeful and reflect the output of the CAN (Kemp & Quintana, 2013). The establishment of a structural network that links neural, autonomic, and cardiovascular areas lays the groundwork for researchers to determine the functional utility of these connections, such as theorizing how they relate to cognitive and emotional processes. One such application of studying these structural relationships is detailed in the Neurovisceral Integration Model.

Neurovisceral Integration Model

The Neurovisceral Integration Model (Thayer & Lane, 2000; 2009) states that adaptive goal-directed behavior depends on communication between central and autonomic components that regulate cardiovascular function. The success of goal pursuit is achieved when neural structures integrate external signals from the environment, internal physiological signals, and past experience in such a way that produces a behavioral pattern that appropriately fits situational demands (Thayer et al., 2012). This conceptualization is highly complementary to the characterization of self-control put forth by other researchers. Broadly speaking, self-control theories aim to explain how a person chooses a behavior and how they regulate their behavior during goal pursuit. There is commonly a conflict between long-term goals and immediate desires, and self-control encompasses the ability to suppress the latter to achieve the former. A core definition of the construct emerges as the cognitive ability to inhibit automatic behavior in

the presence of multiple goals. The Neurovisceral Integration Model provides an explanation of the biological underpinnings of this process.

This theory aims to apply the neurocardiac networks detailed in the CAN to establish a comprehensive framework in which to study how individuals are able to adapt to rapid changes in the environment (Thayer et al., 2012). These structures allow an individual to integrate internal and external signals to adaptively control cognitive, emotional, behavioral, and physiological performance to best meet environmental demands. The system operates to continuously assess the environment for indices of threat or safety, determine appropriate responses, and monitor the coherence between current and desired states to generate motivational efforts that precede behavioral change (Thayer et al., 2012; Thayer & Lane, 2000; 2009). In short, the Neurovisceral Integration Model almost completely defines the conceptualization of self-control-related processes put forth by earlier theories. The striking parallels between the theorized function of the CAN and the characterization of self-control present a strong argument that biomarkers of this model would appropriately fit the construct of self-control more than any other formerly discussed measurement. The authors of the Neurovisceral Integration Model propose that HRV is an optimal biological index of the adaptive regulatory abilities outlined within the theory (Thayer & Lane, 2000; 2009). In this context, HRV may be an ideal biomarker for self-control, which provides support for the relationship between the two constructs and poor psychological health outcomes such as depression.

Heart Rate Variability as a Biomarker

The functional networks of the Neurovisceral Integration Model are highly complex in that neural activity of multiple systems is integrated into gestalt representations of the environment and predicted adaptive responses (Thayer et al., 2012; Thayer & Lane, 2000; 2009).

Thayer and Lane (2000; 2009) sought to identify a physiological index that could determine the degree to which the CAN promotes flexible management and adaptive regulation of its component systems. The authors proposed that HRV is such an index.

To appreciate the potential of HRV as a biomarker of the functional properties of CAN, and correspondingly self-control, principles of the autonomic and cardiovascular systems must first be recalled. The natural unpredictability of the exact rhythm of the heart is rooted in the complex effects of the SNS and PSNS on the intrinsic cardiac nervous system (Reyes Del Paso et al., 2013). The SNS and PSNS exert their influence on the SA node to alter the heart rate in accordance with feedback and current situational contexts. The SA node concurrently receives competing stimulation from both the SNS and PSNS, and the resultant heart rate is determined by the net value of these forces. It is this constant tug of war with the SA node that is thought to be the mechanism that drives the chaotic variability of the heartbeat (Goldberger, 1991).

This interplay defines the positive and adaptive health outcomes that result when these systems are correctly functioning. As long as the SNS and PSNS mutually constrain each other such that their respective inputs to the SA node are balanced, the heart rhythm is inclined to oscillate spontaneously within a range of states in accordance with chaotic dynamics. This balanced control permits the heart to flexibly respond to a range of inputs. In this way, a balanced system promotes positive health outcomes such that the heart rhythm is able to rapidly respond to psychophysiological and environmental demands (Thayer et al., 2012; Thayer & Sternberg, 2006).

While a balance between the SNS and PSNS is implicated in healthy functioning, an imbalance between the two is indicative of dysfunction and disorder. When such a system becomes unbalanced, one component may come to dominate the behavior of the whole system

and it may not appropriately respond to the normal range of inputs (Thayer et al., 2012). Within the ANS, an imbalance between the SNS and PSNS negatively affects the spontaneous oscillatory patterns of the heartbeat such that the heart rhythm becomes more fixed and less flexible. This "locked in" pattern is indicative of dysregulation and a decreased ability to rapidly adapt to environmental changes. The relationship between ANS balance and fluctuations in the heart rhythm supports the notion that HRV is a valuable index of health and regulatory abilities. The heartbeat pattern that results from balanced ANS components oscillates spontaneously, or embodies high HRV, while a pattern that results from an unbalanced system is inclined to oscillate in a fixed manner, or a pattern indicative of low HRV (Thayer et al., 2012).

These dynamic relationships demonstrate that HRV reflects the state of equilibrium among ANS networks and healthy heart function. Considering that these ANS networks are themselves heavily connected with neural systems implicated in the CAN, an argument can be made that the significance of HRV expands past cardiovascular and ANS correlates. Indeed, Thayer and colleagues (2012) theorize that HRV reflects the extent to which central neural systems support and manage adaptive regulatory control over peripheral systems. If true, HRV would be an easily measurable biomarker of the functional networks encompassed within the CAN and the associated ability to operate in complex environments (Thayer et al., 2012). Utilizing HRV as a biomarker in such a way would be a pragmatic approach given the inherent connections between HRV and self-control, HRV and depression, and connections between the three variables.

Heart Rate Variability and Self-control

There is pronounced conceptual, neuroanatomical, and behavioral overlap between HRV and self-control. Conceptually, the principles put forth in Neurovisceral Integration Model are

highly complementary with the theoretical characterization of self-control. The Neurovisceral Integration Model (Thayer & Lane, 2000; 2009) states that adaptive goal-directed behavior depends on communication between central and autonomic components that regulate cardiovascular function. The success of such goal pursuit is achieved when neural structures integrate external signals from the environment, internal physiological signals, and past experience in such a way that produces a behavioral pattern that appropriately fits situational demands (Thayer et al., 2012). Similarly, self-control theories aim to explain how a person chooses a behavior and how they regulate their behavior during goal pursuit. There is commonly a conflict between long-term goals and immediate desires, and self-control encompasses the ability to suppress the latter to achieve the former. A core definition of the construct emerges as the cognitive ability to inhibit automatic behavior in the presence of multiple goals. By applying the CAN, the Neurovisceral Integration Model provides an explanation of the biological underpinnings of these self-control processes and provides evidence that HRV is an appropriate biomarker.

The CAN model details a neuroanatomical network that spans central and autonomic nervous system structures including the PFC, ACC, insula, amygdala, hypothalamus, brainstem nuclei, and the vagus nerve. These structures form a network that harmonize to exert a balanced effect on the heart rhythm that is appropriate for the context at hand. These structures share similarities with the ones implicated in self-control functions. The posited neuroanatomical correlates of self-control were overviewed in a previous section detailing the fMRI and EEG studies associated with the construct. Broadly, self-control abilities have been correlated with the PFC, ACC, insula, striatum, and amygdala (Buhle et al., 2014; Kohn et al., 2014; Ochsner et al., 2012).

More specifically, subsets of these regions have been linked to certain self-control-related functions. Greater rates of reappraisal are associated with decreased activity in the amygdala and increased activity in the dlPFC, dmPFC, vmPFC, and lateral obPFC (Drabant et al., 2009). Reappraisal has been linked to amygdala-PFC functional connectivity as well (Lee et al., 2012). Other studies suggest that the vmPFC is implicated in reward processing, determining the subjective value of behavioral reinforcers, and the consideration of the affective components of imagined future consequences (Bartra et al., 2013; Benoit et al., 2014; Bray et al., 2010). Source localization of EEG components indicates that the dlPFC plays a role in both early suppression of potential distractors and in the modulation of vmPFC activity in self-control-related contexts (Harris et al., 2013). Furthermore, the ACC is implicated in conflict monitoring and regulation of behavioral choices after an error has been made (Bush et al., 2000). The neuroanatomical correlates of self-control described here highly parallel structures implicated in the capacity for goal-directed behavior and regulatory processes put forth in the Neurovisceral Integration Model. Just as the authors of the model suggest that HRV is an appropriate measurement of this complex system, direct links between HRV and self-control further support this premise. Specifically, high frequency HRV (HF-HRV) has been positively associated with PFC activity using several neuroimaging techniques including pharmacological blockades (Ahern et al., 2001), lesion studies (Buchanan et al, 2010), cerebral blood flow (CBF) via positron emission tomography and fMRI (Thayer et al., 2012), and CBF via retinal vessel analysis (Schuster et al., 2014) and pulsed arterial spin labeling (Allen et al., 2015).

Heart rate variability has been linked to self-control with conceptual principles and neuroanatomical correlates thus far, and behavioral connections strengthen the proposition that HRV is an appropriate biomarker of the construct. A significant quantity of psychopathologies

characterized by PFC dysfunction are also characterized by low tonic HF-HRV and excessive HF-HRV reactivity, indicating that HRV is a global biomarker of poor self-control-related abilities (Thayer et al., 2009). High HRV is associated with greater self-control strength and a better ability to exert self-control in demanding situations (Reynard et al., 2011; Segerstrom & Nes, 2007). Furthermore, HRV and performance on tasks of executive function are consistently positively associated. High HRV has been connected to self-control-related abilities such as response inhibition, task switching, attention regulation, and cognitive flexibility (Hansen et al., 2003; Mezzacappa et al., 1998). These associations stand true for measuring HRV at baseline outside the context of a behavioral task (Hansen et al., 2003). Moreover, baseline HRV predicts changes in HRV associated with a behavioral task or reactions to changing environmental demands (Park et al., 2014). The value of HRV as a biomarker for self-control is not contingent on a task-based experimental design, and baseline HRV is apt at discerning individual differences in self-control abilities.

Beauchaine and Thayer (2015) put forth that a specific measurement of HRV, termed high frequency HRV (HF-HRV) serves as a transdiagnostic biomarker of self-control-related functions across externalizing and internalizing syndromes. The authors reported that low HF-HRV is associated with both externalizing and internalizing symptomology, although the former is more consistently associated with HF-HRV than the latter. Internalizing psychopathologies are not universally associated with HF-HRV, and it is more common to observe an interaction between internalizing and externalizing symptomology that more strongly correlates with HRV. Furthermore, comorbid externalizing and internalizing symptomology have predicted greater reductions in phasic HF-HRV during an emotional evocation task compared to either factor alone (Pang & Beauchaine, 2013). The evidence that low tonic (i.e., resting state) HF-HRV and

high phasic (i.e., task-based) HF-HRV reactivity is implicated in such a wide span of disorders suggests that HF-HRV is a general biomarker of impaired self-control-related abilities (Beauchaine 2015a). As discussed in a previous section, Beauchaine & Thayer's (2015) model of psychopathological vulnerability theorizes that individual differences in underlying subcortical networks of BIS/BAS motivational systems interact with cortical networks of self-control to affect behavior. The authors continue that HF-HRV serves as a peripheral index of psychopathology that is globally associated with cognitive dysfunction.

In addition to the above theorized model, several empirical studies, including the ones discussed below, suggest that low HRV is associated with self-control dysfunction in an expansive range of psychopathologies. Individuals with alcohol-use disorders who had low HRV reported a reduced capacity to overcome the urge to drink and an increased attentional sensitivity to alcohol-related cues (Ingjaldsson et al., 2003; Sergerstrom & Nes, 2007). Baseline low HRV has been reported in individuals with ADHD, conduct disorder, aggressive tendencies, and antisocial behavior, syndromes that are characterized by low impulse control (Beauchanie et al., 2001). Further research has established a link between low HRV and uncontrolled eating behavior. Friederich and colleagues (2006) reported that individuals who were obese with a diagnosis of binge eating disorder had reduced HRV under mental duress compared to those who were obese without a binge eating disorder. This finding brings to mind the impact that stress plays in regulatory capacity detailed in the CAPS theory of self-control. The theory posits that the deliberate and contemplative cognitive system is more likely to dominate goal-directed decision making in times of low or moderate stress. Furthermore, during times of stress, behavioral choices are more heavily influenced by the reactive emotional system (Metcalfe & Mischel, 1999). In the study with individuals with binge eating disorders (Friederich et al.,

2006), the case could be made that the stress manipulation decreased the person's capacity for self-control by shifting dominance from the cognitive system to the emotional system. The incidence of low HRV during the stress manipulation suggests that HRV may be an index of this shift in individuals with disorders associated with impaired impulse control. This relationship alludes to the role that stress plays in psychopathologies that are characterized by elements of poor self-control capacity and emotional dysregulation, such as depression.

Heart Rate Variability, Self-control, and Depression

As self-control is related to both depression and HRV, an investigation is merited to determine whether the three constructs are connected with one another. If HRV is indeed a biomarker of self-control, and self-control impairment is implicated in depression, then HRV may be a distal biomarker of depression and its connection with self-control may shed light on how depression relates to ANS dysfunction. Understanding this relationship would improve clinicians' ability to recognize early signs of depression and implement preventative measures such as biofeedback therapy to improve HRV (Bassett et al., 2016).

Autonomic Dysfunction and Depression. The CAN provides an explanation of a complex network of interacting bodily systems that alludes to the notion that the balance between SNS and PSNS influences on the heart rhythm are central to regulatory function throughout the body (Dell'Acqua et al., 2020). From this connection, autonomic dysregulation of the heart rhythm has been studied as a possible pathophysiological mechanism of depression (Hartmann et al., 2019). Studies have reported that depression is commonly associated with autonomic dysfunction, either by increased SNS activity or decreased PSNS activity (Koch et al., 2019). An imbalance between the SNS and PSNS negatively affects the spontaneous oscillatory patterns of the heartbeat such that the heart rhythm becomes more fixed and less flexible. This

"locked-in" pattern is indicative of cardiovascular dysregulation and a decreased ability to rapidly adapt to environmental changes. Indeed, autonomic dysfunction, measured via HRV, has been found in individuals with depression across the lifespan (Brown et al., 2018; Koenig et al., 2016). Moreover, low HRV has been positively associated with depression symptom severity, and HRV changes with alterations in symptom severity (Bassett et al., 2016). Considering that HRV is an index of the functioning of the CAN (Thayer et al., 2012), low HRV may be indicative of dysfunctional neural pathways that relate to the development or persistence of depressive symptoms (Dell'Acqua et al., 2020).

Research has supported the hypothesized relationship between HRV, ANS dysfunction, and depression. Dell'Acqua and colleagues (2020) reported that individuals with previous episodes of depression and those at-risk for developing depression exhibited HRV indices associated with a lack of vagal modulation of the heart rhythm. This finding suggests that ANS dysregulation associated with a vulnerability to depression points to reduced PSNS activity rather than increased SNS activity. Healthy vagal functioning is not only critical in the regulation of the heart rhythm but is also indicative of the robustness of the communication between the adaptive regulatory processes of the brain and the periphery (Dell'Acqua et al., 2020; Thayer & Sternberg, 2006). Consistent with these purported functionalities, reduced PSNS activity is related to poor self-control-related abilities such as emotional regulation and cognitive flexibility, which in turn are associated with a higher risk of depression (Carnevali et al., 2018; Thayer & Lane, 2009)

These studies clearly indicate that ANS dysfunction is connected to the etiology of depression. With this relationship established, an examination of the origins of ANS dysfunction is merited. ANS imbalances can result from a dysregulated stress response system. Fittingly, the

structures and functions implicated in the body's response to stress correlate with those outlined in the CAN and those associated with self-control. By studying the stress response, researchers can learn how dysregulation connects to ANS imbalances and the presentation of depression.

The Stress Response and Depression. The connection between ANS dysfunction and depression can be understood by first examining how a healthy system responds to environmental stressors. A stressor is an event or stimulus that an individual perceives as threatening and triggers a physiological and behavioral stress response (Hilgarter et al., 2021; McEwen & Wingfield, 2003). Successful detection of and appropriate response to a threat is imperative for the survival of an organism. This success depends upon a number of neural systems and structures. Threat appraisal refers to one's ability to correctly assess if a stimulus or situation in the environment is dangerous to their well-being or survival. The amygdala is implicated in the ability to detect relevant stimuli in the environment and rapidly determine its aversive or appetitive value (Holland & Gallagher, 2004; Whalen & Phelps, 2009). The amygdala serves as an initial means of threat appraisal and is suggested to mediate the "fear" response to aversive stimuli (LeDoux, 1996). Although neurons in the amygdala have the ability to encode both positive and negative information, the neurons display a bias towards responding to negative information and encoding negative behavioral outcomes (Cunningham et al., 2008; Paton et al., 2006).

If a threat is detected by the amygdala, the stress response is initiated along the hypothalamic-pituitary-adrenal (HPA) axis. The HPA axis controls a series of neurophysiological processes, such as utilization of glucose as an energy source and the release of cortisol, to respond to stressful stimuli in the environment. As the stressor is detected by the amygdala, the hypothalamus secretes corticotrophin-releasing hormone. This emission causes the

anterior pituitary gland to secrete adrenocorticotrophic hormone, which induces the adrenal glands to release cortisol into the bloodstream. The release of cortisol into the bloodstream causes the person to experience a state of hyper-vigilance, alertness, and responsiveness, such that they are more quickly able to detect and respond to a threat (Tyson, 1998).

The body's response to a stressor is initiated by subcortical areas of the brain such as the amygdala and hypothalamus, but the response can be inhibited or altered by regions of the PFC (Tyson, 1998). The PFC is both anatomically and functionally connected to the amygdala. The interaction between the two regions is crucial in both correctly decoding emotionally salient information and selecting the appropriate behavioral response (Coccaro et al., 2011). Once the amygdala detects a threat, the PFC, especially the medial portion (mPFC) determines if the appraisal was appropriate for the context. If the situation is deemed to be non-threatening or safe, the "fear" reaction of the amygdala is inhibited by the vmPFC thus inhibiting the cascade of subsequent reactions characterized by the stress response. (Thayer et al., 2012).

The vmPFC determines whether to inhibit the "fear" response in the amygdala by drawing from past experiences. The vmPFC is associated with the consolidation and retrieval of safety context memories (Amat et al., 2008). When called upon to determine the validity of the threat appraisal initiated by the amygdala, the vmPFC compares the current situation with similar experienced contexts from the past to inform the decision. Furthermore, the vmPFC is capable of a more sophisticated threat appraisal process than the "quick and dirty" (LeDoux, 1996) method of the amygdala. The vmPFC uses information from long-term memory and perceived control over the threat to decide whether a defensive response is warranted (Maier et al., 2006). This method of cognitive appraisal integrates environmental context with information about past

experiences to inhibit amygdala-initiated stress response circuits if the context is deemed innocuous by the mPFC (Thayer & Siegle, 2002).

Several studies indicate that the vmPFC is required for the ability to exert behavioral control over the stress response by utilizing cognitive appraisal methods to regulate emotion (Eippert et al., 2007; Maier et al., 2006; Milad & Quirk, 2002; Urry et al., 2006). Various types of depressive disorders are associated with hyper-responsiveness of the amygdala in the presence of affective challenges (Etkin & Wager, 2007). These findings indicate that inappropriate stress responses may result from imbalances between the mPFC and amygdala. These imbalances may be rooted in either a hyper-responsiveness of the amygdala or a hypo-responsiveness of the mPFC, the latter of which is indicative of a lack of behavioral control in the face of stressful situations.

The medial obPFC is implicated in emotional regulation of the stress response, specifically regarding socioemotional decision making. Deficits in the medial obPFC have been linked to a decreased ability to accurately identify socioemotional cues such as vocal intonations and facial expressions, two interpersonal indications that are important in assessing the intent of the speaker (Coccaro et al., 2011). Such deficits could lead the individual to make mistakes in moral and ethical decision making when assessing the potential threat of a social interaction. Overall, the neuroanatomical correlates of the stress response overlap with structures associated with self-control-related behaviors and the neurocardiac functional network described in the Neurovisceral Integration Model.

When faced with a potential threat, self-control-related abilities permit the individual to consider mitigating circumstances, or reappraise the situation, such as assigning meaning to ambiguous cues, assuming plausible implications, and employing strategies to adjust emotional

value before reacting (Morawetz et al., 2017). When considering these variables during a decision to exert a behavioral response, PFC regions are engaged that enable the person to inhibit an automatic response to a perceived threat initiated by the amygdala. The successful control of an emotionally driven automatic response to a perceived threat is associated with high HRV. Conversely, low HRV is associated with situations in which a reaction to a perceived threat is not inhibited and the body reacts by initiating the autonomic stress response (Segerstrom & Nes, 2007). In this way, inappropriate appraisals of perceived threats in the environment could repeatedly and unnecessarily activate the body's stress response and produce low HRV. Chronic activation of the stress response, or frequent intervals of stress response activation, contributes to a malfunction of this system including an alteration of autonomic regulation (Hilgarter et al., 2021; McEwen, 1998).

A chronically inappropriate activation of the stress response may lead to ANS dysregulation by disrupting the balance between the SNS and PSNS influences on the heart rhythm. Recall that the SNS responds to severe exercise, fear, or rage, and helps the body prepare for an emergency by stimulating the SA node to increase the heart rate, while the PSNS conserves and restores energy in times when there is no threat detected by stimulating the SA node to decrease the heart rate (Gabella, 2012; Janig, 1989). In healthy individuals, these operations work in concert with complex dynamics intrinsic to the heart to regulate autonomic performance. However, if the body is in a chronic or frequent state of stress, the SNS begins to dominate control over the heart rhythm either due to increased SNS activity or reduced PSNS activity. An imbalance between the SNS and PSNS negatively affects the spontaneous oscillatory patterns of the heartbeat such that the heart rhythm becomes more fixed and less flexible. This "locked in" pattern is indicative of cardiovascular dysregulation and a decreased

ability to rapidly adapt to environmental changes. The heartbeat pattern that results from balanced ANS components oscillates spontaneously, or embodies high HRV, while a pattern that results from an unbalanced system is inclined to oscillate in a fixed manner, or a pattern indicative of low HRV (Thayer et al., 2012).

This account demonstrates that an inability to appropriately respond to environmental cues may relate to an unnecessarily frequent activation of the stress response, which in turn disrupts the balance between the SNS and PSNS that results in low HRV characteristic of depression. Correspondingly, abnormalities in the stress response are found in individuals with depression (Yang et al., 2015). Depression has been associated with a hyperactive HPA axis, elevated cortisol in the blood, a malfunctioning immune response, sleep disturbances, and hypertension (Khan & Khan, 2017; Wong & Licinio, 2001). Furthermore, depressive episodes commonly develop following a negative or stressful life event, and recurrent stress has been linked with the development or worsening of depressive symptoms (McEwen, 2008; Stroud et al., 2008). The temporal relationship between the abnormal stress response and the onset of depression can be supported in either direction; nonetheless, studies clearly indicate that there is a connection between the two constructs.

Establishing a Unifying Connection. The association between HRV, self-control, and depression is supported in multiple ways. Self-control and HRV share neuroanatomical correlates and are each relevant to the etiology of depression. Poor self-control-related abilities are implicated in a reduced ability to appropriately appraise stimuli in the environment to discern the most favorable behavioral response. Individuals must manipulate several simultaneously occurring goals and inhibit behavioral responses that are either inappropriate for the situation or non-congruent with personal goals to do so (Bauer & Baumeister, 2011; Carver & Scheier,

2011). This lack of oversight may result in depressive symptoms following an elevated stress response characterized by low HRV, a hyperactivation of the amygdala, a predisposition to chronic threat perception, and a propensity towards negatively biasing ambiguous cues (Koster et al., 2011; Segerstrom & Nes, 2007; Strauman, 2017).

High HRV and intact self-control abilities indicate adaptive behavioral and physiological responses to moment-to-moment changes in the environment (Thayer & Lane, 2000; 2009). High HRV is partly associated with the PFC and related functions such as self-control via subcortical connectivity. Several studies have demonstrated that this relationship is disrupted in individuals with depression. During an affective set-shifting task, HF-HRV was positively associated with blood oxygenation level dependent (BOLD) activity in the PFC in people without depression, but there was no association between HF-HRV and PFC BOLD activity in those with depression (Lane et al., 2013). Smith et al. (2014) reported that over the course of a 12-week treatment for depression with sertraline, the association between HF-HRV and PFC in those in treatment increased from not significant to positive and no longer differed from those who were not depressed. Lastly, the connectivity between the rostral ACC and the pons was found to be positively associated with HF-HRV and negatively associated with depression symptom severity (Smith et al., 2015). These findings indicate that PFC modulation of subcortical circuits is severely impaired in depression. This dysregulation is relevant to the manifestation of depression according to Beauchaine & Thayer's (2015) model of psychopathological vulnerability, which theorizes that individual differences in underlying subcortical networks interact with cortical networks of self-control to affect behavior. Furthermore, the model puts forth that PFC functioning is a vital protective factor in individuals with vulnerabilities to psychological disorders. It stands to reason that impaired PFC functioning, and accordingly poor self-control-

related abilities, pave the way for the manifestation of depressive symptomology in those who possess underlying vulnerability.

The pathway to depression via poor self-control may be further explained when considering the negative effect of stress. According to theories of self-control, increased stress could impair self-control abilities by hampering the influence of cognitive control systems over decision making and increasing the influence of emotionally charged decision making. This sequence, in turn, could start a cycle in which emotional decision-making further activates the stress response, which further inhibits the cognitive control system. The emotional dysregulation exhibited within this network may lead to depressive symptoms (Yang et al., 2015). Previous research has reported direct links between HRV and depression to further support the relationship between the two constructs. A meta-analysis conducted by Koch and colleagues (2019) indicated that HRV was lower in unmedicated individuals with depression compared to non-depressed controls. Low HRV is an important marker of autonomic imbalance and may have bearing on the presence of stress-related states such as depression (Kemp, Koenig, & Thayer, 2017; Koch er al., 2019)

The utility of HRV as a biomarker of self-control, and more distally, depression, is evident. Although these constructs seemingly connect with one another, additional factors that may influence the relationship should be considered to determine if HRV better serves as a biomarker in some cases rather than others. By examining the potential influence of other factors, a more accurate conceptualization of the relationship may be obtained.

Caveats of HRV as a Biomarker

There is a strong rationale for the argument that HRV is a biomarker for self-control-related abilities. Conceptual, neuroanatomical, and behavioral mechanisms that generate HRV

and self-control have clear connections. However, when put to the test, findings are mixed as to whether HRV is indeed a biomarker for these regulatory processes (Holzman & Bridgett, 2017). Some researchers report that there is a relationship between the two (Capuana et al., 2014; Gentzler et al., 2009; Hansen et al., 2003) others report that no relationship exists (Blankson et al., 2012; Gyurak & Ayduk, 2008; Santucci et al., 2008), while still others report inverse relationships between HRV and self-control (Sturge-Apple et al., 2016). In those who found significant associations, the effect sizes vary widely from study to study, as well (Holzman & Bridgett, 2017). Together, these discrepancies indicate that the link between HRV and self-control is not as straightforward as previously assumed.

Such discrepancies in the literature could result from varying operationalizations of self-control across studies, paralleling the challenges of other indices of the construct that were previously discussed. Another explanation is that additional factors may play a role in the relationship and may influence the ability of HRV to predict self-control capacities in certain ways. Holzman and Bridgett (2017) published a meta-analytic review of potential moderators in the relationship between HRV and self-control in an attempt to answer this question. The authors tested numerous factors that may play a role and identified age as a promising factor to investigate further.

Age as a Moderating Variable

Age may play a role in the capacity of HRV to serve as a biomarker for self-control and depression as the former factor is closely related to the latter three constructs. Several studies have demonstrated that self-control-related abilities evolve over the lifespan. Emotional and behavioral regulatory processes improve from infancy to early adulthood, and the stability of these processes increase into adulthood (Cuevas & Bell, 2010; Garnefski & Kraaij, 2007). Other

studies suggest that self-control abilities related to cognitive reappraisal and behavioral regulation may decline in older age starting in mid-adulthood (Opitz et al., 2012). As previously mentioned in the description of the CAPS theory of self-control, the emotional system's influence on decision making is dominant earlier in life, and as a person's PFC develops with age, the cognitive system impacts decision making more often (Metcalfe & Mischel, 1999). Indeed, increases in top-down regulation of behavioral choices are associated with the continued development of the PFC into adulthood and there is a decline in PFC-mediated functioning at older ages (Sowell et al., 2004). Together, these studies suggest that individual differences in self-control abilities may in part be a function of age, and that examining age may provide a better understanding of how self-control relates to HRV across the adult lifespan.

There are age-related differences in ANS functioning and HRV as well. The regulation of the ANS declines with age and the development of this imbalance is evident in several ways. As previously discussed, the heart's rhythm is determined by action potentials generated at the SA node in response to PSNS and SNS input. SA node dysfunction increases in prevalence with age and is common in older adults (Moghtadaei et al., 2016). Specifically, 1 in 600 people over the age of 65 exhibit SA dysfunction and this condition is the most common reason for the need for an artificial pacemaker (Moghtadaei et al., 2016). In addition, the time it takes for the neurons of the SA to repolarize and reset to respond to the next action potential increases with age (Cho, 2016).

The healthy functionality of the ANS decreases linearly with age, but the PSNS functionality exhibits a U-shaped pattern (Almeida-Santos, Barreto-Filho, Oliveira, Reis, Oliveira, & Sousa, 2016). Almeida-Santos and colleagues found that PSNS function decreased from ages 40 to 60, hit the lowest point in the 7th decade, and increased again at age 80

(Almeida-Santos et al., 2016). Additionally, PSNS modulation of heart rate declines at an earlier and more rapid rate than SNS modulation starting in the sixth decade of life (Umetani et al., 1998).

These indicators of ANS imbalances are attributed to decreased vagal modulation of the heart with age, which is quantified by measuring HRV. Age-related changes in vagal modulation are primarily influenced by age itself and not other physiological variables associated with the aging process, such as fitness, triglycerides, cholesterol, glucose, and systolic blood pressure (Fukusaki et al., 2000). Not only does HRV decrease with aging (Kumral et al., 2019; Voss et al., 2015), but low HRV influenced by less vagal modulation on heart rate is associated with increased morbidity in older adults (Tsuji et al., 1994).

High HRV is associated with healthy aging (Zulfiqar et al., 2010) and better health outcomes (Kemp & Quintana, 2013). Specifically, high HRV is related to a lower risk of cardiovascular diseases (Thayer et al., 2010), reduced mortality (Buccelletti et al., 2009), and better cognitive performance (Zeki Al Hazzouri, 2014). Thus, HRV is considered a biomarker for healthy aging (Kumral et al., 2019).

The Neurovisceral Integration Model posits that frontal, subcortical, and ANS pathways interact to regulate the heart rhythm (Thayer et al., 2012). The PFC inhibits subcortical areas and the ANS, thus playing a prominent role in PSNS influences at the SA node via the vagus nerve. Following this logic, the model suggests that individual differences in HRV may reflect structural and functional changes in the brain (Thayer et al., 2012; Kumral et al., 2019).

Several studies support the notion that HRV is an indicator of age-related changes in brain health. For example, resting HRV is positively associated with the thickness of ACC, lateral obPFC, mPFC, and posterior cingulate cortex (Winkelmann et al., 2017; Yoo et al., 2018).

In one study that assessed the heart-brain connection across the lifespan, high HRV was related to stronger functional connectivity between the amygdala and mPFC, and age-related differences were reported between the amygdala and lateral PFC (Sakaki et al., 2016).

Furthermore, Kumral and colleagues (2019) reported that the neural correlates of resting HRV are age-dependent using resting-state functional connectivity analyses.
The authors grouped participants into three age groups: young (26 +/- 4.2 years), middle-aged (46.3 +/- 6.2 years), and older (66.9 +/- 4.7 years). Across all age groups, HRV was positively associated with network centrality in the posterior cingulate cortex. In the vmPFC, network centrality was positively associated with HRV in the young cohort but not in the middle-aged or older cohorts. The latter finding supports the ideas put forth by the functional plasticity hypothesis of cognitive aging (Greenwood, 2007), such that age-related structural vulnerability of brain areas, especially the PFC, leads to a reorganization of functions to compensate for the structures that deteriorate. Kumral and colleagues (2019) suggest that their finding that the declining regulation between vmPFC and HRV with age is indicative of altered cardiovascular function via PSNS and vagal influences. As increasing age is associated with a deterioration of neurocardiac structures across the CAN, it stands to reason that age may be a valuable factor to consider when deciphering discrepancies in the literature pertaining to the utility of HRV as a biomarker for self-control.

The findings related to the lifespan trajectory of self-control abilities, PFC connectivity associated with self-control, and neurocardiac networks associated with HRV substantiate the notion that age may moderate the relationship between HRV and self-control-related constructs. Holzman and Bridgett (2017) conducted a meta-analytic review to investigate the merit of such a relationship. Given the developmentally related modification of connectivity between the PFC

and neurocardiac networks, the authors postulated that the greater refinement of this connectivity from childhood to adulthood and the decrease in interconnectivity in older age indicates that the strength of the relationship between HRV and self-control-related constructs may be a function of age (Holzman & Bridgett, 2017). Indeed, previous research has reported that compared to younger adults, older adults have weaker associations between HRV and the functional connectivity of the PFC and amygdala (Sakaki et al., 2016). Results of a meta-regression analysis in the meta-analytic review support this notion as well (Holzman & Bridgett, 2017). Here, the authors reported a significant linear relationship between age and the relation between HRV and self-control-related constructs. This research indicates that age may moderate the effect of HRV on self-control, but samples in the meta-analytic review did not include adults over the age of 55. Studies that examine this complex relationship in a sample of adults across the lifespan, specifically with the inclusion of older adults, must be conducted to better determine the moderating effect of age on HRV and self-control across the adult lifespan.

Increased age is not only associated with poorer HRV, regulatory abilities, and neurocardiac network connectivity but with depression as well. The onset of depression with increasing age may be associated with a rise in negative life events commonly experienced in older adulthood such as debilitating medical disorders, loss of loved ones, less control over activities of daily living, and an inability to partake in once-regular activities (American Psychological Association, 2021). These stressors, along with potentially less social support than in earlier years, may put one at heightened risk of experiencing depression. Furthermore, cognitive impairments such as processing speed, neurological factors such as white matter hyperintensities, and autonomic dysfunction evidenced by low HRV are evident in older individuals with depression (Vasudev et al., 2011). The variation in autonomic, neurocognitive,

and psychological functioning that is associated with age suggests that age may clarify the relationship between HRV and self-control and how the constructs relate to depression.

Conclusion

The appropriate detection and response to stressful external factors are indicative of adaptive regulatory abilities and healthy psychological functioning. Neurocardiac structures and circuits ensure that the body adjusts to changing situational demands, and self-control capacities allow for the inhibition of inappropriate behavioral responses to those demands. In such a complex regulatory system, there are many opportunities for errors to occur. Malfunctioning components may have drastic effects on a person's ability to suitably react to the environment and may have detrimental effects on psychological wellbeing. Poor self-control, or the inability to inhibit inappropriate behavioral responses, and low heart rate variability, are both indicative of a decreased capacity to respond to environmental demands. In turn, low heart rate variability is associated with a predisposition to chronic threat perception, amygdala hyperactivation, and a negative bias towards ambiguous cues, which are also implicated in the manifestation of depression. The overlapping characteristics of these factors, in addition to the shared influence of increasing age, merits an investigation into this relationship to determine how underlying aspects of psychophysiological dynamics contribute to the manifestation of poor health outcomes.

CHAPTER 2: CURRENT STUDY

The current study examined the nature of the relationship between HRV, self-control, age, and depression. Archival self-report and physiological data from the Midlife in the United States (MIDUS) online database were utilized to answer the following three research questions. First, this study aimed to investigate whether HRV was a biomarker of self-control. Identifying biomarkers improves researchers' ability to predict, diagnose, and monitor signs of impairment (Mayeux, 2004), and recognizing physiological correlates of self-control may aid in our understanding of the etiology of related psychological disorders. HRV may be a prudent biomarker of self-control as both low HRV and low self-control share overlapping neuroanatomical correlates (Thayer & Lane, 2000; 2009), both are indicative of an inability to adaptively react to changing environmental demands (Porges, 1996), and both are associated with poorer psychological health (Hansen et al., 2003; Strauman, 2017). It was hypothesized that HRV was positively related to self-control, such that low HRV was associated with lower scores on a self-control self-report measure, and vice versa.

Second, this study aimed to determine if identifying HRV as a biomarker for self-control contributed to our understanding of the etiology of depression. Self-control and HRV may be connected to the incidence of depression through a maladaptive stress response (Yang et al., 2015). During this response, the individual assesses and chooses a response to detected environmental threats. Self-control allows the individual to manipulate several simultaneously occurring goals and inhibit behavioral responses that are either inappropriate for the situation or non-congruent with personal goals (Bauer & Baumeister, 2011; Carver & Scheier, 2011). The detection of a threat not only engages self-control abilities, but it also impacts the heart rhythm

and HRV. During a healthy response, the heart rate increases in the presence of a threat and decreases in the absence of a threat or once the threat is resolved. High HRV is indicative of a person's ability to quickly shift the heart rhythm to adapt to these changing environmental demands (Porges, 1996). Low HRV, or a decreased ability to adapt one's physiological state to the environment, is associated with a predisposition to chronic threat perception, amygdala hyperactivation, and a propensity towards negatively biasing ambiguous cues (Segerstrom & Nes, 2007). These three factors parallel those indicated in the etiology of depression (Koster et al., 2011; Strauman, 2017). In the current study, it was hypothesized that self-control mediated the relationship between HRV and depression. Specifically, it was suggested that low HRV would be associated with low self-control, which would in turn be related to higher scores on a depression self-report measure, and vice versa.

Lastly, the current study aimed to ascertain if age played a role in how HRV, self-control, and depression relate to one another. Previous studies have established that age is a significant factor for each of these variables separately. In particular, both self-control and HRV decrease with age, and individuals with depression present with low HRV, especially in older age (Kumral et al., 2019; Sowell et al., 2004; Vasudev et al., 2011; Voss et al., 2015). Although the factors of HRV, self-control, age, and depression are associated with one another, they had yet to be investigated concurrently within a single study. It was hypothesized that increased age would be associated with a weaker relationship between HRV and self-control, which in turn would relate to higher instances of depression.

Statement of the Problem

The current study examined the nature of the relationship between HRV, self-control, age, and depression. First, this study aimed to investigate whether HRV was a biomarker of self-

control. Second, this study aimed to determine if identifying HRV as a biomarker for self-control contributed to our understanding of the etiology of depression. Lastly, the current study aimed to ascertain if age played a role in how HRV, self-control, and depression related to one another. Three hypotheses were put forth to address each of these aims.

Hypothesis 1: HRV is positively associated with self-control

Self-control is the ability to inhibit undesired behaviors to comply with environmental demands or personal goals (Bauer & Baumeister, 2011; Carver & Scheier, 2011). Impairments in self-control are common and people are often unable to control their behavior in various contexts (Baumeister & Heatherton, 1996; Baumeister et al., 1994). Furthermore, self-control dysfunction is prevalent in various psychological disorders, such as depression (Strauman, 2017).

Due to the prevalence of self-control impairments in psychological disorders, researchers have sought to examine this construct using several methodologies to better understand the connection to poor psychological health outcomes. There is a wide array of measures available to researchers to assess self-control. The choice of methodology is often one of the greatest challenges when seeking to examine the construct. Behavioral, self-report, and neuroscientific methods exist for researchers to choose from, but there are limitations to each. Behavioral tasks often assess a number of executive functions in concert without isolating self-control. Over 100 self-control self-report measures exist, but the most commonly used ones have limitations as well (Duckworth & Kern, 2011). These measures weakly converge with behavioral tasks, and the choice of questionnaire accounts for 53% of the variance in effect size when assessing self-control (Duckworth & Kern, 2011). Lastly, neuroscientific methods such as event-related fMRI and EEG require high expense and training. Similar to one of the drawbacks of behavioral measures, the task-based design of these neuroscientific studies may not isolate self-control.

With self-control being at the center of so many disorders of dysregulation, researchers must continue to search for optimal ways to measure this construct.

One additional way to measure self-control is through cardiovascular measures, specifically HRV. The Neurovisceral Integration Model states that adaptive, goal-directed behavior depends on an integration of neural networks spanning between the central and autonomic nervous systems tasked with regulating cardiovascular function (Thayer & Lane, 2000; 2009). Crosstalk across these networks is supported by the Central Autonomic Network, which details the neuroanatomy and neurocircuitry that connects areas of the PFC with subcortical areas and the brainstem, which in turn influence the variation between heartbeats, or HRV, in response to the environment (Benarroch, 1993; Kemp & Quintata, 2013).

Using HRV as a biomarker for self-control would be a better method than the others previously mentioned. The cortical areas that correlate with self-control abilities, such as the vmPFC and anterior cingulate cortex, are prominent components of the Neurovisceral Integration Model and Central Autonomic Network that directly influence beat-to-beat heart rhythms (Thayer et al., 2012). Thus, there is a direct overlap in neuroanatomical features that influence both HRV and self-control. Because of this overlap, it is likely that measuring HRV would be a more direct means of isolating self-control from other executive functions. Second, low HRV is associated with several psychological disorders and reflects a poor ability to adapt to changing environmental demands (Hansen et al., 2003; Shaffer et al., 2014). Poor self-control is similarly characterized as an inability to exert behaviors that are congruent with the environment. As both poor HRV and poor self-control are thought to be reflective of an inability to adaptively react to the environment, HRV should theoretically correlate with self-control. This study aimed to test the merit of HRV as a biomarker for self-control with this hypothesis.

Hypothesis 2: Self-control mediates the relationship between HRV and depression

Low HRV and low self-control are indicative of an inability to adaptively react to changing environmental demands and are associated with poorer psychological health (Coyne & Gotlib, 1983; Shaffer et al., 2014; Strauman, 1992). One such outcome of both low HRV and self-control abilities is depression (Carnevali et al., 2018). Low HRV, poor self-control, and depression have overlapping neuroanatomical, behavioral, and emotional correlates and consequences. As part of the threat response, abilities of the PFC (i.e., executive functions) are critical in the assessment of the validity of the detected threat and to conjure an appropriate behavioral response. Part of this decision-making process entails the exercise of self-control capacities, which allow the individual to manipulate several simultaneously occurring goals and inhibit behavioral responses that are either inappropriate for the situation or non-congruent with personal goals (Baumeister & Heatherton, 1996; Baumeister et al., 1994). The detection of a threat influences changes in HRV, as the heart rate increases in the presence of a threat and decreases in the absence of a threat or once the threat is resolved (Segerstrom & Nes, 2007). Low HRV, or an inability to adapt one's physiological state to the environment, is associated with a predisposition to chronic threat perception, amygdala hyperactivation, and a propensity towards negatively biasing ambiguous cues. (Segerstrom & Nes, 2007). These three factors parallel those indicated in the etiology of depression (Koster et al., 2011; Strauman, 2017). Furthermore, previous research has indicated that depression is associated with low HRV, especially in older individuals (Bassett et al., 2016; Vasudev et al., 2011). Identifying HRV as a biomarker for self-control and linking the association to depression-related outcomes provides a better understanding of the cognitive, physiological, and emotional regulatory dysfunction that characterizes the disorder. To this end, it was hypothesized that self-control mediated the

relationship between HRV and depression, such that low HRV would be associated with low self-control, which in turn would be associated with higher endorsement of depression. Correspondingly, high HRV was hypothesized to relate to high self-control, which would, in turn, correlate with less endorsement of depression.

Hypothesis 3: Age moderates the relationship between HRV and self-control, such that increased age increases the effect of HRV on self-control in the association with depression

Self-control and HRV share neuroanatomical correlates and are both prevalent in numerous psychological disorders, including depression (Thayer & Lane, 2000; 2009). HRV may be a more direct measure of self-control abilities due to overlapping anatomical structures and because both are indicative of an inability to rapidly respond to environmental demands. However, studies that have examined the relationship between self-control and HRV reported mixed findings (Holzman & Bridgett, 2017). The discrepancies in the literature point to the possibility that moderating factors influence this relationship.

Age appears to be a factor that may strengthen or weaken the relationship between HRV and self-control. Increased age is associated with both lower HRV and lower PFC self-control abilities due to structural changes in neurocardiac structures (Kumral et al., 2019; Sakaki et al., 2016). Specifically, age-related changes in HRV are accompanied by changes in the functional connectivity of cortical structures implicated in self-control, including the vmPFC and cingulate cortex (Kumral et al., 2019; Sakaki et al., 2016). Age may help explain the discrepancies in the literature that exist when examining HRV and self-control on their own and may drive this relationship.

Age has been previously examined in this context, as a moderating variable between HRV and self-control, but mixed findings exist here as well. Sometimes age moderates the

relationship and sometimes there is no significant effect (Holzman & Bridgett, 2017). Theoretically, age should have a relationship between HRV and self-control due to the connections discussed above. The discrepancies may exist due to methodological issues within the age variable. The studies that have examined age in this context previously have not included samples of adults across the lifespan. Studies have examined adolescents compared to adults overall, but no study has compared the effect of age across the span of adulthood. Including older adults and comparing them to middle-aged and younger adults may explain why age is sometimes a moderating variable and sometimes is not in previous studies. If the effect of age on the HRV-self-control relationship is stronger in older age, then grouping adults into one single category may have hidden the effects. This study aimed to examine age across the lifespan as an improvement to previous similar studies to better determine the role of this factor.

Summary

To summarize the findings surrounding age, self-control, HRV, and depression: low HRV and poor self-control are both indicative of an inability to adaptively respond to environmental demands. Both constructs have a relationship that may be influenced by age, such that as age increases, the strength of the connection between HRV and self-control increases. Low HRV and depression are both categorized by a predisposition to chronic threat perception, amygdala hyperactivation, and a propensity towards negatively biasing ambiguous cues. Depression, particularly in older adults, is associated with low HRV. Overall, these four main constructs under investigation have connections with one or more of each other but have yet to be investigated concurrently within a single study. An examination of these four constructs within a single study provides a more comprehensive understanding of how the four are interrelated. A relationship between the four would suggest that HRV is a biomarker not only of

self-control but may also be considered a biomarker of depression via self-control. Furthermore, examining the role of self-control provides a better understanding of the connection between low HRV and age-related changes in depression.

CHAPTER 3: METHODS

Participants

Data for this study was archivally collected from a publicly available online database called the Midlife in the United States (MIDUS) Refresher Study Survey (Dienberg Love et al., 2010). The original MIDUS project was a national survey that began in 1994 and enlisted more than 7,000 Americans aged 25 to 74.

Potential participants were initially identified by phone by random digit dialing. Inclusion criteria for participating in MIDUS included being an adult above the age of 25 and living in the continental United States. Participants were recruited from three regions of the United States and were assigned to a site based on their region. Those in the West Coast region were assigned to UCLA, those in the Midwest region were assigned to the University of Wisconsin, and those in the East Coast region were assigned to Georgetown University. IRB approval was obtained for each of the three study sites.

The purpose of the MIDUS study was to explore behavioral, psychological, and social factors to better understand age-related differences in physical and mental health. With continued funding from the National Institute on Aging, additional projects arose from MIDUS, including the MIDUS 2 Refresher Study Survey conducted from 2011-2014. This refresher survey re-recruited 3,577 adults from the original sample. Part of the refresher survey included the gathering of biological data samples from 863 respondents via the Refresher Biomarker Project. This project branch aimed to integrate biological assessments with psychosocial factors to gain a more comprehensive understanding of health outcomes in a representative sample of adults from across the continental United States. Selected data from the participants in the MIDUS 2

Refresher Study Survey who also completed the Refresher Biomarker Project was used in the current study.

The current study started with a baseline *n* of 863 adults who completed both the MIDUS 2 Refresher Study Survey and the Refresher Biomarker Project. Certain cardiovascular and neurological health factors were considered as exclusion criteria. Participants with medical or psychiatric disorders that produce autonomic dysfunction were excluded (Myers et al., 2018; RenuMadhavi & Ananth, 2012; Young & Benton, 2018). These comorbidities included myocardial infarction, atrial fibrillations, ischemic cardiomyopathy, coronary heart disease, hypertension, cardiac arrhythmia, heart failure, presence of an artificial pacemaker, diabetes, hypothyroidism, severe brain injury, schizophrenia, post-traumatic stress disorder, bipolar disorder, Parkinson's disease, multiple sclerosis, and epilepsy. Excluding for these variables resulted in a final *n* of 593 (M_{age}=51.16, SD_{age}=13.33, 287 female).

General Procedure

Staff at each site mailed the study information to potential participants in their respective regions and individuals were informed that they would receive $200 compensation for participating. If the participant agreed to join the study, study site staff obtained verbal consent, made travel arrangements, and scheduled the visit. Participants stayed overnight in the Clinical Research Center of their site to collect data and all meals were provided. Upon arrival, written consent was obtained and data collection commenced. The data collection protocol was standardized across sites.

When participants arrived on day 1, they provided information regarding their current medications and personal history, they completed a long version of the physical examination, and began a 12-hour urine collection period. Personal history information that was collected

included change in marital status, death of close friends or family members, physical symptoms and conditions, major health events (broken bones, surgeries, head injuries, joint injuries, motor vehicle accidents, and amputations). The long version of the physical exam included integument of hair and skin, hearing, sinuses, mouth, neck (range of motion, tenderness, thyroid), cardiovascular function (auscultation, murmurs, pulses), thorax and lungs (inspection, auscultation), musculoskeletal function (muscles, spine, joints, tender points, extremities), and neurological function (coordination, motor system, reflexes, sensation, autonomic). Furthermore, they completed the Self-Administered Questionnaire that contained psychosocial measures pertaining to mood, depression, perceived stress, anger, anxiety, childhood trauma, positive events, relational-independence, social obligations, sympathy, adjustment, support/strain given to others, self-control, and quality of life in America.

On day 2, the 12-hour urine collection period ended, a fasting blood draw was obtained, participants completed the Psychophysiology Experimental Protocol, and they completed a short version of the physical examination. This shorter physical examination included collecting vital signs (height, weight, pulse, blood pressure, respiration, temperature), obtaining waist and hip measurements, and completing functional assessments (grip strength, visual acuity, peak flow, 50-foot timed walk, chair stands). The Psychophysiology Experimental Protocol entailed measurements of heart rate variability, respiration, saliva cortisol, and beat-to-beat blood pressure before, during, and after two six-minute cognitive challenges and one six-minute orthostatic (standing) challenge. Resting heart-rate variability at baseline was procured from this dataset for use in the current study. The procedure for the measurement of baseline heart-rate variability is described in detail below.

Heart Rate Variability Procedure

Participants were instructed not to consume caffeine or nicotine after midnight the night before the physiological data collection session. Electrocardiograph (ECG) electrodes were placed on the left and right shoulders and on the lower left quadrant of the midsection. Bands were placed around the chest and abdomen to measure respiration. To measure blood pressure, a Finometer (Finapres Medical Systems, 2012) blood pressure cuff was placed on the middle finger of the non-dominant hand, and a Finometer blood pressure arm cuff was placed on the upper non-dominant arm. Participants were seated in a comfortable position while experimenters calibrated the monitoring devices. Following calibration, participants were instructed to sit quietly during the 11-minute baseline for the continuous recording from the ECG and Finometer devices.

Measures

Participants completed self-report measures pertaining to demographics, medical history, self-control, and psychological health, as well as heart rate variability measurements, that were used in the current study. Please see Appendix A for a list of questions included in each of the self-report measures.

Self-Administered Questionnaire

Participants were asked to provide personal demographic information and a medical history in a self-report questionnaire. Age is the single variable from this form that was used in primary analyses. It was expected that age would be negatively associated with both self-control and HRV. A history of disorders and health circumstances was obtained from each participant's record to exclude for these factors in analyses. Specifically, the following factors were excluded due to their association with autonomic irregularities: myocardial infarction, atrial fibrillations,

ischemic cardiomyopathy, coronary heart disease, hypertension, cardiac arrhythmia, heart failure, presence of an artificial pacemaker, diabetes, hypothyroidism, severe brain injury, schizophrenia, post-traumatic stress disorder, bipolar disorder, Parkinson's disease, multiple sclerosis, and epilepsy.

Self-Control Scale

The Self-control Scale (SCS; Gross & John, 2003; Markus & Curhan, 2011; Markus & Kitayama, 1991) is a 19-item measure that quantifies aspects of self-control including cognitive control, emotional control, and burden consciousness. Mean scores were calculated for analyses. It was expected that HRV was positively associated with scores on the SCS.

Center for Epidemiological Studies-Depression Scale

The Center for Epidemiological Studies-Depression Scale (CES-D; Radloff, 1977) is a 20-item measure that quantifies symptoms of depression experienced over the past week. The answer choices are presented as a Likert scale ranging from 0 to 3 (0 = *Rarely or None of the Time*; 1 = *Some or Little of the Time*; 2 = *Moderately or Much of the Time*; 3 = *Most or Almost All the Time*). The total score was calculated as a sum of all 20 responses, with the range of scores being between 0 and 60. Scores of 16 or greater suggest risk for clinical depression, with higher scores indicating greater risk. The measure can be used across a wide array of ages (Lewinsohn et al., 1997) and ethnicities (Roth et al., 2008). It was expected that HRV and scores on the SCS would be negatively associated with scores on the CES-D.

Heart Rate Variability

The ECG and Finometer devices collected data continuously throughout the 11-minute baseline period and produced raw waveform data. The data was processed according to standardized algorithms (Task Force, 1996). To process ECG signals, beat-to-beat analog signals

were digitized at a sampling rate of 500 Hz and a 16-bit resolution with a microcomputer equipped with a National Instruments analog-to-digital (A/D) board. ECG waveforms were submitted to proprietary event detection software to identify R waves. Research staff then visually reviewed the ECG waveforms to manually correct any errors made by the software. These normal RR intervals were used to calculate cardiac variables including HRV.

HRV can be measured via time domain analyses to determine the amount of variance within the timing between successive RR intervals (Shaffer et al., 2014). The RR interval can be used to calculate any of the following parameters that are commonly used in analyses: the standard deviation of the RR interval (SDRR), the standard deviation of the RR interval means for each 5-minute segment of a recording (SDARR), the mean of the standard deviations of all RR intervals within each 5-minute segment of a recording (SDRR index), and the percentage of adjacent RR intervals that differ from each other by more than 50 milliseconds (ms) (pRR50). Additionally, the root mean square of successive differences between normal heartbeats (rMSSD) can be calculated from the RR interval. To calculate the RMSSD, the time difference between each RR interval is calculated, and each of these time differences is squared. Those values are then averaged together, and the square root of that total is acquired. The RMSSD is the primary method used in time domain analyses to determine PSNS and vagally stimulated changes in HRV (Shaffer et al., 2014).

Frequency domain or power spectral analyses of HRV measurements are also employed. Power spectral analyses separate the HRV oscillation into separate rhythms that exist within different ranges of frequencies. While time domain analyses produce output pertaining to the characteristics of the temporal latency of HRV, frequency domain analyses can determine the variance and amplitude (i.e., power) of a rhythm as a function of its time period (i.e., frequency)

(Shaffer et al., 2014). The heart rate oscillations are divided into four separate frequency bands: high-frequency (HF; 0.15-0.5 Hz), low-frequency (LF; 0.04-0.15 Hz), very-low-frequency (VLF; 0.0033-0.04 Hz), and ultra-low-frequency (ULF; <0.0033 Hz) (Task Force, 1996).

In the MIDUS 2 Refresher Biomarker Project, time domain indices of SDRR and rMSSD were calculated, as well as LF and HF frequency domain indices. For frequency domain analyses, the spectra of RR interval series were calculated using an interval method for computing Fourier transforms (DeBoer et al., 1984). To compute the Fourier transforms, the mean of the RR interval series was subtracted from each value in the series. Then, the series was filtered using a Hanning window (Harris, 1978), and lastly, the power (variance in ms^2), over the LF and HF bands was summed. Estimates of spectral power were adjusted to account for attenuation produced by this filter (Harris, 1978). Following standard practice in HRV research, natural log-transformed versions of the variables were computed. Natural log-transformed variables are commonly sought as they produce a reliably skewed distribution.

Data Analysis

Quantification of Self-control

Self-control was quantified as a single continuous variable calculated from total scores on the SCS. Higher scores on the SCS indicated better self-control.

Quantification of Heart Rate Variability

The current study utilized the natural log-transformed HF-HRV variable as the measure of HRV. HF-HRV is strongly associated with PSNS functioning; specifically, HF-HRV is an index of vagal influence on the sinoatrial node of the heart (Sandercock et al., 2008). Conversely, LF-HRV is associated with both SNS and PSNS activity (Vasudev et al., 2011). The isolation of PSNS activity is desired in the current analyses for a number of reasons. The PSNS, via the vagal

nerve, inhibits the heart rate as needed and high PSNS is implicated in healthy cardiovascular regulation (Jennings & Yovetich, 1991). Furthermore, the PSNS is positively related to cognitive functions of the PFC, including self-control (Thayer et al., 2009). Higher HF-HRV values are reflective of higher HRV. It was expected that HRV was positively associated with scores on the SCS and negatively associated with scores on the CES-D.

Quantification of Depression

Depression was quantified as a single continuous variable from total scores on the CES-D. Higher CES-D scores were indicative of more depressive symptoms.

Quantification of Age

Age was quantified as a single continuous variable gathered from the Self-Administered Questionnaire.

Primary Analyses

All data was analyzed using the statistical software R (R Core Team, 2020). A series of models were employed to determine the relationship between HRV, self-control, depression, and age. To test Hypothesis 1, a simple linear regression was employed with HRV as the predictor variable and SCS scores as the outcome variable. The lavaan package (Rosseel, 2012) in R was used to test the path analyses in Hypotheses1, 2 and 3. The lavaan package is a collection of tools used in R to explore and estimate latent variable modeling and multivariate statistical models, such as path analyses, confirmatory factor analyses, structural equation modeling, and growth curve models (Rosseel, 2012). A path analysis was then used to test the mediation model in Hypothesis 2. Here, HRV was the predictor variable, CES-D scores were the outcome variable, and SCS scores were the mediating variable. Indirect effects were examined. Third, age was added to the path analysis as a nested model to test the moderated mediation model in

Hypothesis 3. All variables were centered prior to calculating the interaction term for moderation analyses. The variables in this third model were in the same roles as in Hypothesis 2, and age was added as a moderator variable between HRV and SCS scores. The presence of a significant moderating effect was measured by examining the strength of the interaction term and the relationship between differing levels of the moderator and the indirect effects.

Data Processing

Missing Data

Structural equation modeling (Hoyle, 1995) was used to determine the relationship between the variables in the models, and as such, an approach to account for missing data must be appropriate for this methodology. Missing data was accounted for with the full information maximum likelihood (FIML) approach using the lavaan package in R (Rosseel, 2012). This approach was optimal for the current data structure as structural equation modeling was employed to test the hypotheses, all variables within the analyses were continuous, and all missing data was assumed to be missing at random (Newsom, 2020). FIML uses likelihood functions to account for missing data. A likelihood function is a method to determine the model fit, or the discrepancy between observed data and the model-implied (i.e., expected) data. If there is a lower discrepancy between observed and expected data, the model is deemed to have a good fit, and the opposite is true if there is a higher discrepancy (Myung, 2003). The likelihood function is used to estimate the combination of expected data values that maximizes the probability of drawing the observed data. With FIML, a likelihood function was calculated based on the variables that were present for each individual. These functions were then summed across participants to determine overall model fit (Newsom, 2020).

Calculation of Standard error

The standard error indicates how spread out the data is around the mean. The bootstrap standard errors of the models were calculated and reported in the current study. This index is the standard deviation of the bootstrap samples and is an estimate of the standard deviation of the sampling distribution of the mean. The bootstrap standard error determines how accurately the means of the bootstrapped samples estimate the population mean. A smaller value indicates a more accurate estimate of the expected value, while a larger value indicates a less accurate estimate (Efron & Tibshirani, 1986).

Calculation of Indirect Effects

Indirect effects were calculated for the mediation and moderated mediation models tested for Hypotheses 2 and 3, respectively. In models without mediating variables, the direct effect of a predictor variable on an outcome variable is determined (see Figure 1a below). Mediation models test the effect of the predictor variable that works through a specified intermediate variable, or the mediator (Hafeman, 2009) (see Figure 1b below). For example, the mediation model of Hypothesis 2 in the current study determines if the relationship between the predictor variable, HRV, and the outcome variable, depression, is explained by the mediating variable, self-control. The effect of the predictor variable on the outcome variable that works through the mediating variable is the indirect effect. A conceptualization of path models with and without a mediating variable is depicted in Figure 1.

The indirect effect is calculated by multiplying the regression coefficient of the effect of X on M, or the *a* path, with the regression coefficient of the effect of the M on Y, or the *b* path (Edwards, 2012). The magnitude of *ab* communicates the amount of mediation that occurs in the

relationship between X and Y through M (Edwards, 2012). A larger value for *ab* indicates a larger indirect effect, and vice versa. The indirect effect is correspondingly termed *ab*.

The criteria put forth in the causal steps procedure were followed such that mediation was assumed to exist if the *c'*, *a*, and *b* paths were significant, and if *c'* was significantly smaller or nonsignificant compared to *c* (Baron & Kenny, 1986). The mediation may be either full or partial. A full mediation indicates that the whole effect of X on Y is transmitted through M; that is, X has no direct effect on Y when M is included in the model as evidenced by a non-statistically significant *c'* path and a significant *ab* value. A partial mediation indicates that X has both direct and indirect effects on Y, as evidenced by a statistically significant *c'* path and *ab* value. In partial mediation models, both the direct relationship between X and Y without M exists as well as the indirect relationship between X and Y through M (Edwards, 2012).

Moderated Mediation Path Model. The moderated mediation path model tested in this study for Hypothesis 3 posited that the mediating effect of M in the relationship between X and Y is moderated by a variable W (Baron & Kenny, 1986). A conceptualization of the moderated mediation path model is depicted in Figure 2.

In moderated mediation models, the indirect effect depends on the moderator. The indirect effect of X on Y through M is the product of X on M and the effect of M on Y, which is a function of W (Hayes & Rockwood, 2019). The weight of W is the index of moderated mediation in this model (Hayes, 2015). If there is no relationship between W and the size of the indirect effect, it can be concluded that the mediation of M on X and Y is not affected by W.

The current study employed the subgroup approach to test the moderated mediation path model as this method is recommended for structural equation modeling (Rigdon, Schumaker, & Wothke, 1998). The sample was split into subgroups that represent different levels of W, and

mediation was examined within each subgroup using the causal steps procedure (Wegener & Fabrigar, 2000). In this study, the mediation was examined at the mean level of W, one standard deviation above the mean of W, and one standard deviation below the mean of W, resulting in three subgroups. If the support for a mediation model differed between the subgroups as evidenced by direct and indirect effects, it could be concluded that the mediation is moderated by W (Edwards & Lambert, 2007). In other words, the moderating variable altered the capacity of M to explain the relationship between X and Y. To describe these relationships with variables from the current study, consider Hypothesis 3. Here, it was suggested that self-control mediated the relationship between HRV and depression, and age moderated the relationship between HRV and self-control. If a significant moderated mediation exists, it can be concluded that age either accentuates or attenuates the effect of HRV on self-control, which in turn alters the effect of self-control on depression.

Interpretation of Analyses

The interpretation of the analyses will focus on effect sizes and asymmetric confidence intervals to determine the scope of the difference between groups. Effect sizes allow the researcher to determine the magnitude of the difference between the groups and are less reliant on sample size than *p*-values. As examples, a large effect may be detected with a small sample size, and a large sample size is more likely to result in a significant *p*-value, but the difference between the groups may have a negligible effect regardless (Sullivan & Feinn, 2012). In the current study, Standardized betas were used to interpret the analyses. Effect size magnitudes were interpreted using the following limits: Small effect = 0.1, Medium effect = 0.3, Large effect = 0.5 (Cohen, 1988).

Confidence internals not only convey statistical significance, but they also report the range of possible effect sizes. These estimates are useful in interpreting how likely it is that the study captured the true effect size given the size of the difference observed between the groups (Davies & Crombie, 2009).

Although not central to interpretation of the models, *p*-values were reported in the results when appropriate. Statistical significance tests such as *p*-value estimates report whether or not the findings are likely to be significant due to chance. These estimates are prone to error and solely convey if there is an effect or not (Sullivan & Feinn, 2012). The use of *p*-values to interpret results is not optimal for path models that include indirect effects, such as in mediation and moderated mediation models. In these types of models, the product of two normal regression coefficients (i.e., *ab* path or indirect effect) is not normally distributed (Ryu & Cheong, 2017). Accordingly, the standard method of determining significance with *p*-values lacks statistical power and alternatives that more accurately encompass the true distribution of the indirect effect should be employed. The current study used the recommended practice of calculating bias-corrected bootstrapped confidence intervals based on 1,000 bootstrapped samples to produce asymmetric confidence intervals (ACIs). The 95% ACIs were calculated, and an indirect effect was considered significant if the 95% ACI did not contain zero. The *p*-values will not be reported for model components that include indirect effects and will only be reported for variable relationships with direct effects. In these instances, a *p*-value of ($\alpha = 0.05$) will indicate a statistical significance. It is important to note that reported *p*-values were not adjusted for multiple comparisons as these values were not used as central components of the interpretation of results.

CHAPTER 4: RESULTS

Descriptive statistics and bivariate correlations pertaining to the variables were computed and are reported in Tables 1 and 2, respectively. The R script that was generated to perform the analyses is contained in Appendix B.

Primary Analyses

Hypothesis 1: Association between HF HRV and Self-control

A simple linear regression was employed to determine the association between HF HRV and scores on the SCS. Results indicate that there was a significant relationship between HF HRV and SCS scores, and the effect size was small (b=0.045, p=.027, r=.107, 95% ACI [0.006, 0.085]). Specifically, for every one unit increase in HF HRV, the expected SCS scores rose by 0.045 units. This finding suggests that there is a positive association between HF HRV and self-control, yet this relationship is somewhat weak. Results for Hypothesis 1 are presented in Table 3 and Figure 3.

Hypothesis 2: Mediation Analysis

Scores on the SCS were entered into a path analysis model as the mediating variable between HF HRV and scores on the CES-D. The indirect effect was examined to determine the role of self-control within the relationship between HF HRV and depression. The direct and indirect effects of the model suggest that self-control fully mediates the effect of HF HRV on depression. The direct effect of HF HRV on depression (i.e., *c'* path) was not statistically significant (b=0.200, p=.295, r=.051, 95% ACI [-0.218, 0.538]), while the effects of HF HRV on self-control (i.e., *a* path) (b=0.044, p=.033, r=.104, 95% ACI [0.004, 0.087]), self-control on depression (i.e., *b* path) (b=0.989, p=.028, r=.106, 95% ACI [0.137, 1.942]) and the indirect

effects (*b*=0.043, *r*=.011, 95% ACI [0.003, 0.118]) suggest the presence of a mediated relationship. It is important to recall that higher scores on the CES-D are indicative of more depression-related symptoms, thus a positive statistical relationship between the scores and HRV and self-control is equivalent to an inverse relationship conceptually. The small effect sizes for the *a* and *b* paths and the negligible effect size reported for the indirect effect indicates that the effect of HF HRV on depression that is explained by self-control is not particularly strong regardless of statistical significance. Results for Hypothesis 2 are presented in Table 4 and Figure 4. See Appendix C for model results with scores on each of the four subscales of the CES-D as the outcome variable instead of the total score.

Hypothesis 3: Moderated Mediation Analysis

The moderated mediation path analysis model determined whether age moderated the effect of HF HRV on self-control, and if the interactions related to depression. The only statistically significant piece of the model was the relationship between self-control and depression, although the effect size was small (*b*=1.051, *p*=.018, *r*=.113, 95% ACI [0.295, 2.021]). No other components of the model suggested statistical significance or a notable effect size. Overall, these findings indicate that age does not moderate the effect of HF HRV on self-control to further relate to depression. Results for Hypothesis 3 are presented in Table 5 and Figure 5.

Summary of Primary Analyses

Results supported Hypothesis 1 in that HF HRV was significantly related to self-control, such that higher HF HRV values were associated with higher reports of self-control. Hypothesis 2 was supported as well, in that self-control mediated the relationship between HF HRV and depression. Lastly, the null results of the moderated mediation model did not support Hypothesis

3. According to these findings, age did not significantly affect the effect of HF HRV on self-control and more distally depression. As emphasized throughout this section, the reported effect sizes for each of the tests were trivial. Thus, although Hypotheses 1 and 2 were supported, the relationships between the variables were weak and may be better explained through different means.

CHAPTER 5: DISCUSSION

Human behavior is guided by a desire to attain certain goals. Some goals that we pursue are immediately gratifying, and others require patience and self-control to enjoy rewarding effects in the long term. Time and time again, we must manipulate the pursuit of multiple goals simultaneously and decide how to navigate our environments to support the desires we most value. As with many other complex cognitive functions, failures of self-control are common and struggles emerge as psychopathologies characterized by emotional and cognitive dysregulation, namely depression. The injurious relationship between poor self-control and the manifestation of depression is critical to target in order to better predict, understand, diagnose, and treat indices of dysfunction, yet the precise nature of the relationship between self-control and depression is insufficiently understood. A critical restraint in the study of self-control is the lack of appropriate measurement tools accessible to researchers and the lack of identified biomarkers that comprehensively reflect the functional neural networks that facilitate self-control-related functions. The current study employed a novel approach to investigate the nature of the relationship between self-control and depression that benefitted from the incorporation of HRV, a robust neurocardiac biomarker of self-control-related abilities. Findings supported the merit of HRV as a biomarker of self-control and revealed that self-control fully mediated the relationship between HRV and depression. It was expected that age played a role in this relationship due to the changing lifespan trajectories of neurocardiac networks interconnected with self-control and depression, although this premise was found to be unsupported. These discoveries deepen our understanding of the neurocognitive and autonomic dynamics of depression and supplicate

clinical researchers aiming to decrease dysfunction to entertain approaches supported by a biopsychological perspective.

HRV as a Biomarker of Self-control

The current study first aimed to investigate whether HRV was a biomarker of self-control. It was hypothesized that HRV would be positively related to self-control. Results of a simple linear regression support this hypothesis such that low HRV was associated with lower scores on a self-control self-report measure, and vice versa. In the model tests for the three main hypotheses, asymmetric confidence intervals (ACIs) and effect sizes were used over *p*-values to determine the significance and magnitude of the relationship between the variables. While the ACIs of the model that tested Hypothesis 1 suggest a significant relationship, it is important to take the small effect size into account when determining the overall bearing of the association between the two variables. The results suggest that HRV is a biomarker of self-control, but that this connection is not particularly strong. Theoretical and methodological factors should be considered to account for the significant yet insubstantial findings of this model.

The significant relationship inferred from this model test is consistent with theoretical conceptualizations of HRV as a biomarker of self-control. HRV is theorized to reflect the output of the Central Autonomic Network (CAN). This network models a complex series of cortico-subcortical circuits that ultimately control beat-to-beat changes in the heart rhythm which characterizes HRV (Kemp & Quintana, 2013). The establishment of a structural network that links neural, autonomic, and cardiovascular areas supports a comprehensive framework that may help to explain how individuals are able to adapt to rapid changes in the environment (Thayer & Lane, 2000; 2009; Thayer et al., 2012). The structures within this network allow an individual to integrate internal and external signals to adaptively control cognitive, emotional, behavioral, and

physiological performance to best meet environmental demands. The system operates to continuously assess the environment for indices of threat or safety, determine appropriate responses, and monitor the coherence between current and desired states to generate motivational efforts that precede behavioral change (Thayer et al., 2012; Thayer & Lane, 2000; 2009).

The parallels between the theorized function of the CAN and the characterization of self-control present a strong argument that biomarkers of this model would appropriately fit the construct of self-control above other measurements. The Neurovisceral Integration Model endorses HRV as a physiological index that determines the degree in which the CAN promotes flexible management and adaptive regulation of its component systems (Thayer and Lane, 2000; 2009). The success of such goal pursuit is achieved when neural structures integrate external signals from the environment, internal physiological signals, and past experience in such a way that produces a behavioral pattern that appropriately fits situational demands (Thayer et al., 2012). The purported functions of HRV mirror several theories of self-control as previously discussed. Overall, self-control is defined in these theories as a set of abilities that determine how a person chooses a behavior and how they regulate their behavior during goal pursuit. Identifying HRV as a biomarker of self-control would provide a more comprehensive explanation as to how self-control, a set of abilities thought to be relegated to PFC regions, is able to coordinate with cortical and autonomic structures to ultimately influence behavioral patterns.

In addition to conceptual similarities, there is significant overlap in the neural structures and connections identified in the CAN and those associated with self-control-related abilities, most notably the obPFC, vPFC, and the functional connectivity of the amygdala-PFC (Drabant et al., 2009; Lee et al., 2012). Lastly, the index of HRV used in the current study, HF HRV, is a measure of the PSNS influence on the heart rhythm. The functioning of this branch of the ANS is

positively associated with cognitive functions of the PFC, including self-control (Thayer et al., 2009).

Overall, the finding in the current study that HRV is a biomarker of self-control is supported by previously determined conceptual and neuroanatomical overlaps between self-control and HRV. Moreover, the quantification of HRV used in the current study is most associated with PFC functions such as self-control and behavioral studies have reported a significant positive relationship between HRV and self-control-related abilities (Reynard et al., 2011; Segerstrom & Nes, 2007; Thayer et al., 2009).

The identified relationship between HRV and self-control carries several implications. The field is in need of a biomarker or other measurement tool of self-control that exhibits high construct validity. Behavioral tasks that aim to assess self-control either assess a number of executive functions without isolating self-control, or only assess some aspects, such as temporal discounting (Duckworth & Kern, 2011). Self-report measures weakly converse with behavioral tasks, and the choice of measure has been found to account for 53% of variance in the effect size (Harris et al., 2013). Lastly, neuroscientific biomarkers identified with fMRI and EEG methodologies have drawbacks as well. These measurements often come with high expense and training, and if dependent on task-based designs, may not isolate self-control (Hofmann, 2015).

Findings widely support the notion that self-control is not a function isolated to a single brain area and may best be conceptualized with a network approach. A biomarker measurement such as HRV that reflects the various regions associated with self-control, including PFC regions, ACC, amygdala, and others in a single integrated network may be the resolution. The demonstration that HRV relates to self-control in the current study lends support for the wider use and integration of HRV in investigations of self-control and how the biomarker of the

construct relates to other psychological or neurocognitive factors associated with self-regulatory abilities.

Although the statistical significance of the relationship between HRV and self-control was supported via ACIs, the small effect size should be considered when discerning practical applications of the finding. The small effect size indicates that the relationship between the two variables is somewhat weak and that there may be limited practically meaningful differences in self-control in people with varying levels of HRV. The strong theoretical support of a relationship between the two constructs suggests that methodological shortcomings may have played a significant role in the size of the model effect. As stated above, self-report measures of self-control are not optimal as they weakly converge with behavioral tasks and the measure choice has been found to account for 53% of the variance in effect size (Harris et al., 2013). The use of a self-report measure in general to quantify self-control could have contributed to the small effect size between the construct and HRV. A better validated self-report measure may have positively affected the effect size in the model and underscores the importance of choosing an appropriate measure to quantify self-control.

The findings of the model tested in Aim 1 are meaningful in that they may encourage the use of HRV as a proxy for self-control without the supplementation of other measures that may skew or misrepresent the results due to lower predictive validity. However, before such steps are to be made, research that investigates the types of validity of HRV must be considered. Indeed, studies have reported that the length of time that HRV is recorded affects the predictive validity of the measure (Shaffer et al., 2020). Long-term HRV measurements ($\geq$ 24 hours) are more strongly attributed to fluctuations in the circadian rhythm, core body temperature, and the sleep cycle (Task Force, 1996). Furthermore, these long-term measurements are more useful when

examining the SNS components of HRV, while short term (~5 minutes) measurements can identify the interaction between the PSNS and SNS and isolate the PSNS effect on the heart rhythm. Research has indicated that short-term values correlate poorly with long-term counterparts and that short-term values often have less predicative power (Bigger et al., 1989). The length of time of a recording is an important consideration and suggests that further research may be required before HRV is accepted for widespread use to predict health-related outcomes.

The current study employed resting state recordings of HF HRV that were 11 minutes in duration. The length of time of the recording appears appropriate for the research questions at hand as the current study sought to isolate PSNS influence on the heart rhythm. However, the shorter duration may have negatively impacted the predicative power of the measure and may have influenced the model results. Furthermore, the differences in predicative validity depending on time of recording limits the generalizability of the current findings. Determining the characteristics of HRV measurement that are optimal for the research question at hand while not sacrificing predicative power is an important area of focus for future studies.

While it is apparent that variations in measurement characteristics significantly impact the association of HRV with other outcomes, the evidence from the current study suggests that significant relationships do exist and may serve to offer a basis for the field to continue to investigate the intricacies involved in utilizing HRV in clinical research. The verification of HRV as a biomarker of self-control is critical in the pursuit of answering questions related to determining the significance of self-control in regulatory disorders. The connection between self-control and disorders of cognitive and emotional regulation has been established, but the nature of the relationship remains elusive. It is unknown if multiple pathways exist that lead to the development of self-control difficulties, or if early biological difficulties with self-control

predisposes an individual to the incidence of later behavioral difficulties and poor symptom management (Strauman, 1992). Examining the physiological correlates of poor self-control with a biomarker such as HRV can aid in the understanding of how the construct is connected to psychopathologies characterized by emotional dysregulation, specifically depression.

The results from the model tested in Aim 1 suggests that HRV is a biomarker of self-control, but that the practical significance of the relationship may be limited. The theoretical basis of the connection is supported from previous research and methodological limitations may have played a significant role in the weak relationship between the two constructs that was suggested from the current study. The importance of continuing to explore the utility of HRV as a biomarker of self-control lies in the opportunity to gain a better understanding of the nature of the relationship between self-control and psychopathology.

Self-control as a Mediator between HRV and Depression

The second study aim was to determine if identifying HRV as a biomarker for self-control contributed to our understanding of the manifestation of depression. It was hypothesized that self-control would mediate the relationship between HRV and depression. Results of a path analysis model support this hypothesis such that self-control fully mediated the effect of HRV on depression. Specifically, higher HRV was associated with higher self-control, which was negatively associated with depression symptoms, and vice versa. There was no significant direct effect between HRV and depression with self-control as a mediator, indicating that the entire association between HRV and depression is transmitted through self-control. The ACIs of this current model support the statistical significance between the variables but the effect sizes were small for the *a* and *b* paths and negligible for the indirect effect. The results suggest that self-control mediated the relationship between HRV and depression but that this association was not

of particular strength or practical significance. Theoretical and methodological factors should be considered to account for the significant yet somewhat ineffectual findings of this model.

The significant associations inferred from this model test are consistent with the theoretical notion that HF HRV signifies a biomarker for poor self-control abilities implicated in psychopathological disorders. A significant quantity of psychopathologies characterized by PFC dysfunction are also characterized by low tonic HF-HRV and excessive HF-HRV reactivity, suggesting that HRV is a global biomarker of poor self-control-related abilities irrespective of specific symptomology (Thayer et al., 2009).

Beauchaine and Thayer (2015) additionally put forth a theory that HF HRV serves as a transdiagnostic biomarker of self-control-related functions across psychopathological syndromes. Their model unfolds a pathway that links HRV, self-control-related abilities, motivational systems, and the manifestation of externalizing/internalizing disorders. The underlying motivational networks of BIS and BAS are important to consider first. In brief, BAS is associated with reward seeking and approach motivation and is mediated by the mesolimbic dopamine pathway. BIS encompasses aversive motivational behaviors such as passive avoidance of threat and is theorized to be the neural substrate of trait anxiety. BIS is mediated by the septo-hippocampal system that includes serotonin and noradrenaline projections (Gray, 1982, 1987).

Beauchaine and Thayer (2015) express in their model that individual differences in BIS and BAS, and the interaction between the two systems, suggest differing vulnerability to psychopathologies. Low mesolimbic dopamine is associated with a hyperactive BAS and impaired reward processing. This makeup is in turn implicated in traits such as high impulsivity, high irritability, and greater risk of depression-related symptoms (Laakso et al., 2003). High BIS is associated with higher risk of depression-related symptoms, correlates with higher risk of

anxiety, and is not typically implicated in high trait impulsivity (Neuhaus & Beauchaine, 2013). These relationships indicate that BIS and BAS individually contribute to the manifestation of maladaptive personality traits; however, the interaction between BIS and BAS is more directly related to the presentation of externalizing or internalizing disorders. Specifically, individuals with high BAS and low BIS are more likely to manifest symptom clusters consistent with externalizing disorders, while those with low BAS and high BIS are more likely to manifest symptom clusters consistent with internalizing disorders (Beauchaine & Thayer, 2015). These relationships are important to understand how underlying neurobiological variations lead to individual differences in motivation, which contribute to the development of specific personality traits and finally contribute to vulnerability to externalizing or internalizing disorders.

The BIS/BAS motivational networks may serve as etiological substrates to increased vulnerability to externalizing and internalizing disorders, but it is this higher vulnerability coupled with poor self-control that is theorized to be the pathway to psychopathology (Beauchaine & Thayer, 2015). This conceptualization pairs well with the three theories of self-control discussed in the introduction. These theories put forth that self-control is a cognitive and affective process, and that cognitive abilities serve to override a more automatic decision-making process that is often emotionally charged, reflexive, or immediately gratifying. Accordingly, poor self-control acts as the catalyst of the development of psychopathology in those who were at increased risk.

Attention should be paid to the presentation of depression that is associated with high BAS, deficient mesolimbic dopamine functioning, and subsequent maladaptive reward processing. This pathway to depression overlaps with deficient reward processing associated with poor self-control. As noted above, low levels of mesolimbic dopamine that are implicated in

individual with high BAS may result in high trait impulsivity or depression impulsivity (Laakso et al., 2003). Previous sections of this manuscript have compared the overlap between impulsivity and self-control. While some theories purport that self-control and impulsivity uniquely predict behavior (Duckworth & Kern, 2011; Tangney et al., 2004), others characterize self-control as the inverse of impulsivity (Potenza & de Wit, 2010; Reynolds et al., 2006). Although the current study conceptualizes self-control and impulsivity as separate constructs, the argument could be made that the neurobiological substrates of maladaptive reward processing associated with high impulsivity, depression, and poor self-control are related. If this conceptualization is accurate, a clear link can be made between poor self-control and the manifestation of depression that can be traced to a shared quality of maladaptive reward processing.

Thus far, the interpretation of the model put forth by Beauchaine and Thayer (2015) has connected self-control-related abilities with motivational systems and the manifestation of externalizing/internalizing disorders. The final component to consider to apply to the current study is the significance of HRV within this pathway. HF HRV has been associated with both externalizing and internalizing syndromes and their interaction (Beauchaine 2015a). Accordingly, the authors of the model have suggested that HF HRV serves as a peripheral index of psychopathology that is globally associated with cognitive dysfunction Beauchaine and Thayer (2015).

Beauchaine and Thayer's model (2015) provides a theoretical explanation of the model results in the test for Hypothesis 2 of the current study. Results indicate that HRV is associated with depression through self-control. This relationship reflects the theorized connections between the three constructs. Poor self-control is a catalyst for the manifestation of depression in

those who have premorbid vulnerabilities, and HRV serves as a biomarker of self-control dysfunction associated with depression.

Self-control is a complex cognitive function that incorporates past experiences, future outcomes, and situational context in the pursuit of goal-directed behavior in an effort to prioritize long-term values over immediate temptations. Failures of self-control are directly implicated in the emergence of psychopathologies characterized by emotional and cognitive dysregulation, namely depression. Recognizing the relationship between poor self-control and the manifestation of depression is critical to better predict, understand, diagnose, and treat indices of dysfunction, yet the precise nature of the relationship between self-control and depression is insufficiently understood. A critical setback in the study of self-control and its connection with depression is the lack of measurement tools and identified biomarkers that comprehensively reflect the functional neural networks that facilitate healthy self-control-related abilities. Without the appropriate tools to measure this relationship, clinical researchers may have an incomplete or inaccurate picture of how these constructs connect, which may in turn hinder prevention and intervention efforts that aim to improve quality of life in those with depression. Likewise, improved measurement tools and biological indices have the potential to advance current practices or promote the development of new ones that better fit the conceptualization of how self-control relates to depression. The findings that HRV relates to depression via self-control support the use of HRV as a biomarker of poor self-control associated with depression. Future studies would benefit from utilizing HRV in this context to gain a deeper understanding of the neurocardiac and neurocognitive substrates of depression. Understanding this relationship would improve clinicians' ability to recognize early signs of depression and implement preventative measures (Bassett et al., 2016).

The results of this model further support the argument that HRV is a biomarker of self-control that was examined with the first aim of the current study. The link between HRV and depression supported by self-control augments the utility of HRV in psychobehavioral research in that HRV indices are valuable tools to explore intermediate factors of psychopathology. Even so, the small effect sizes from the model indicating an overall weak relationship between the variables temper the practical applications of these findings. Continued investigations into the dynamics between the three constructs may deliver more robust conclusions that would merit the implementation of these discovered principles into interventional and preventative care.

The model tested in Aim 2 suggests that HRV relates to depression through self-control, but that the practical significance of the relationship may be minimal without further research. Conceptual notions and neurobiological substrates potentially connect maladaptive goal directed behavior that is evident in both poor self-control functioning and depression. The inclusion of measures that assess personality and motivational tendencies may further validate the connection between HRV, self-control, and depression. The complex relationship between HRV, cognitive function, motivation, and externalizing/internalizing syndromes highlight the utility of adopting a biopsychological perspective of psychopathology.

Age as a Moderator in the Relationship between HRV, Self-control, and Depression

The third study aim was to determine the role of age in the relationship between HRV, self-control, and depression. It was hypothesized that increased age decreased the effect of HRV on self-control, which in turn related to higher instances of depression. Results of a moderated mediation path analysis model did not support this hypothesis. Age did not significantly moderate the effect of HRV on self-control in any way to further relate to depression.

The examination of the potential of age as a moderator on the effect of HRV on self-control and its relationship with depression was a novel question, but previous research supports the significance of age as a moderator on the effect of HRV to self-control-related abilities. Holzman and Bridgett (2017) conducted a meta-analytic review to investigate the merit of such a relationship. Given the developmentally related modification of connectivity between the PFC and neurocardiac networks, the authors postulated that the greater refinement of this connectivity from childhood to adulthood and the decrease in interconnectivity in older age indicates that the strength of the relationship between HRV and self-control-related constructs may be a function of age (Holzman & Bridgett, 2017). Indeed, previous research has reported that compared to younger adults, older adults have weaker associations between HRV and the functional connectivity of the PFC and amygdala (Sakaki et al., 2016). Results of a meta-regression analysis in the meta-analytic review support this notion as well (Holzman & Bridgett, 2017).

From these findings, the current study sought to expand the scope of what had previously been investigated by inquiring whether depression was a distally related outcome in the association between HRV, self-control and age. Age has been demonstrated to be separately related to the other three constructs. Several studies have demonstrated that self-control-related abilities evolve over the lifespan. Emotional and behavioral regulatory processes improve from infancy to early adulthood, and the stability of these processes increase into adulthood (Cuevas & Bell, 2010; Garnefski & Kraaij, 2007). Other studies suggest that self-control abilities related to cognitive reappraisal and behavioral regulation may decline in older age starting in mid-adulthood (Opitz et al., 2012).

There are age-related differences in ANS functioning and HRV as well. SA node dysfunction increases in prevalence with age and is common in older adults (Moghtadaei et al.,

2016). In addition, the time it takes for the neurons of the SA to repolarize and reset to respond to the next action potential increases with age (Cho, 2016). These indicators of ANS imbalances are attributed to decreased vagal modulation of the heart with age, which is quantified by measuring HRV. Age-related changes in vagal modulation are primarily influenced by age itself and not other physiological variables associated with the aging process, such as fitness, triglycerides, cholesterol, glucose, and systolic blood pressure (Fukusaki et al., 2000). Not only does HRV decrease with aging (Kumral et al., 2019; Voss et al., 2015), but low HRV influenced by less vagal modulation on heart rate is associated with increased morbidity in older adults (Tsuji et al., 1994).

Several studies support the notion that HRV is an indicator of age-related changes in brain health. For example, resting HRV is positively associated with the thickness of ACC, lateral obPFC, mPFC, and posterior cingulate cortex (Winkelmann et al., 2017; Yoo et al., 2018). In one study that assessed the heart-brain connection across the lifespan, high HRV was related to stronger functional connectivity between the amygdala and mPFC, and age-related differences were reported between the amygdala and lateral PFC (Sakaki et al., 2016). Furthermore, Kumral and colleagues (2019) reported that the neural correlates of resting HRV are age-dependent using resting-state functional connectivity analyses. Kumral and colleagues (2019) reported that the declining regulation between vmPFC and HRV with age is indicative of altered cardiovascular function via PSNS and vagal influences. As increasing age is associated with a deterioration of neurocardiac structures across the CAN, it stands to reason that age may be a valuable factor to consider when deciphering discrepancies in the literature pertaining to the utility of HRV as a biomarker for self-control.

Lastly, increased age is not only associated with poorer HRV, regulatory abilities, and neurocardiac network connectivity but with depression as well in some instances. Cognitive impairments such as processing speed, neurological factors such as white matter hyperintensities, and autonomic dysfunction evidenced by low HRV are evident in older individuals with depression (Vasudev et al., 2011).

The separate connections between age and the other three constructs of interest including HRV, self-control, and depression prompted the current investigation to examine the four factors together within a single model. However, results indicated that no significant relationship exists with the hypothesized model configuration. Future studies should aim to explore the role of age within these associations in different ways.

The findings of the model tested for Hypothesis 3 indicate that age does not directly affect the effect of HRV on self-control. Although neurocardiac networks associated with both HRV and self-control change throughout the lifespan, results indicate that the strength of the relationship between HRV and self-control does not fluctuate with adult age. The lack of a moderating effect may strengthen the value of HRV as a biomarker of self-control as the association does not appear to falter with increasing age in adulthood.

Limitations

The insignificant findings related to age as a moderator of the effect between HRV and self-control in the current study warrant considerations of the merit of alternative operationalizations of age. The index of age used in the current study was chronological age, or the number of years since birth. This quantification has been exclusively used to study the HRV-self-control connection. However, biological age, or the accumulation of an individual's health deficits (i.e., diseases, disabilities, psychosocial function, and anatomical or physiological

abnormalities), may be a better indicator of overall health than chronological age, especially in aging populations (Jazwinski & Kim, 2019). The model results for Hypothesis 3 may have suggested more significance if biological age is indeed a stronger moderator in this relationship than chronological age. From a measurement perspective, if biological age is indeed a stronger moderating variable than chronological age, future studies ought to include the former in analyses when conducting research within these fields.

Another limitation that must be addressed is the lack of racial and ethnic diversity in the study sample. ~90 percent of the study sample identified as White, followed by ~5 percent identifying as Black or African American, and the rest identifying as Native American/Alaskan Native, Asian, or Native Hawaiian/Pacific Islander (see Table 1). Because the study sample was not representative of the overall population, not only is the generalizability of findings limited but the results may have differed with a more racially diverse sample. Previous research has shown that race plays a key role in how people think and interact with others (Roberts et al., 2020). Race is a social construct and is linked to several social factors such as access to resources, interracial contact, social norms, and socioeconomic status, that ultimately affect psychological phenomena (Roberts et al., 2020). Furthermore, studies have reported ethnic differences in resting heart rate variability (Hill et al., 2015) and depression (Bailey, Mokonogho, & Kumar, 2019). Future research should replicate the current study with a more representative sample to determine if the findings differ or not.

A third limitation of the current study is the conceptualization and quantification of depression as a pathognomic and unitary entity. Pathognomic classification systems, such as the DSM-5, posit that the presence of certain symptoms is consistently indicative of a specific psychological disorder and that they share a common etiology. An alternative to this system is

non-pathognomic models, which suggest that psychological disorders that appear to present as a single diagnosis at the behavioral level may arise from multiple different etiological pathways. These models adopt a dimensional approach, such that specific psychopathological syndromes are the result of differing levels of functional interactions between multiple neurobehavioral systems (Beauchaine & Thayer, 2015).

Research has indicated that pathognomic models of depression may impede the progression of the field. As examples, efforts to identify neurobiological mechanisms of depression are often heterogeneous and may not be the same across individuals, and differences in pathophysiological mechanisms suggest that treatment options of antidepressants are more favorable when considered on an individual level (Buch & Liston, 2021). The quantification of depression with a more dynamic model may have significantly altered the results of the current study as neurobiological elements of the relationship between the variables were considered. Future studies should implement these more progressive models of depression to achieve a deeper understanding of the nuanced association between the constructs.

Future Research

A number of future directions have been alluded to throughout the discussion, but three more should be addressed. This study implemented a mediation model to assess the relationship between HRV, self-control, and depression. However, the design of the current study constrained the interpretation of the results. All data was collected concurrently in one session. A concurrent mediation model has a much more limited ability to suggest the causal effects of one variable on another compared to a longitudinal mediation model (Jose, 2016). A longitudinal study considers that the causal relationship between two or more variables takes time to develop and may not happen instantaneously (Selig & Preacher, 2009). With this shortcoming in mind, replication of

the current study with longitudinal data would be a better investigation of the idea that these variables are indeed causally related, and predicative of depression. Specifically, data pertaining to HRV should be gathered prior to data about self-control, and then data about depression should be gathered. In this way, there would be greater evidence that HRV is a predictor of self-control, which in turn, should be a predictor of depression.

Future studies should differently consider the role of age in the context of HRV, self-control, and depression. The current study hypothesized that age was a moderator such that increased age increased the effect of HRV on self-control and more distally depression; however, model results did not support this relationship. Age was considered as a moderating variable due to evidence of such from previous research (see Holzman & Bridgett, 2017 for a meta-analytic review). Alternative conceptualizations of the function of age as a variable of interest may provide more robust findings and future research would benefit from such adjustments.

There is a wide variety of measures available to researchers to assess self-control. The choice of methodology is often one of the greatest challenges when seeking to examine the construct. Behavioral, self-report, and neuroscientific methods exist for researchers to choose from, but there are limitations to each. The current study investigated the merit of HRV as a superior biomarker and measurement tool of self-control. However, the recognition of HRV as a useful measure is still in development and studies would benefit from including multiple measures of self-control concurrently within a single study. Future studies may seek to employ a latent variable analysis with several measures to explore the relationship between available choices and provide insight into which measures are more valuable than others.

Table 1
Descriptive Statistics

Variable Name	Percent	Mean	Standard Deviation	Variance	Standard Error of the Mean	Minimum	Maximum	Range
Age	-	51.16	13.33	177.66	0.55	26	78	52
Biological Sex		-	-	-		-	-	-
Female	48.40							
Male	51.60							
Race		-	-	-		-	-	-
White	90.56							
Black or African American	4.64							
Native American or Alaskan Native	1.56							
Asian	0.55							
Native Hawaiian or Pacific Islander	0.14							
Other	2.55							
Ethnicity		-	-	-		-	-	-
Not Hispanic or Latinx	96.95							
Hispanic or Latinx	3.05							
Life Events Checklist	-	3.16	2.46	6.06	0.11	0	16	16
SCS Score	-	4.94	0.57	0.32	0.02	3.21	9.21	6
CES-D Score	-	15.36	5.28	27.88	0.22	0	45	45
CES-D Score without Somatic subscale	-	11.97	3.33	11.10	0.14	0	31	31
Log transformed HF-HRV	-	5.22	1.34	1.79	0.06	0.51	9.25	8.75

Table 2
Bi-variate Correlations

Variable	*M*	*SD*	1	2	3	4	5
1. Age	51.16	13.33					
2. HF HRV	5.22	1.34	-.41** [-.48,-.34]				
3. SCS Scores	4.94	0.57	-.08* [-.16,-.00]	.10* [.02,.19]			
4. CES-D Total Scores	15.36	5.28	-.11** [-.19,-.03]	.07 [-.02,.15]	.11** [.03,19]		
5. CES-D Scores without Somatic Complaints Subscale	11.97	3.33	-.05 [-.13,.03]	.03 [-.06,.12]	.08* [.00,.16]	.87** [.85,.89]	
6. Life Events	3.16	2.46	.15** [.06,.23]	-.09* [-.19,-.00]	.04 [-.05,.12]	.19** [.11,.27]	.17** [.09,.26]

Note. M and *SD* are used to represent mean and standard deviation, respectively. Values in square brackets indicate the 95% confidence interval for each correlation. * indicates $p < .05$. ** indicates $p < .01$.

Table 3
Model Results for Self-control on HF HRV

Variable	*b*	S.E.	*p*-value	Std. β	CI lower	CI upper
HF HRV	0.045	0.020	0.027	0.107	0.006	0.085

Note. S.E. refers to the standard error, Std. β refers to the standardized beta CI refers to the asymmetric confidence intervals.

Table 4
Model Results for HF HRV Relating to Depression via Self-control

Variables	*b*	S.E.	*p*-value	Std. β	CI lower	CI upper
Depression on						
HF HRV	0.200	0.190	0.295	0.051	-0.218	0.538
Self-control	0.989	0.450	0.028	0.106	0.137	1.942
Self-control on						
HF HRV	0.044	0.021	0.033	0.104	0.004	0.087
Indirect Effect	0.043	0.029	-	0.011	0.003	0.118

Note. S.E. refers to the standard error, Std. β refers to the standardized beta CI refers to the asymmetric confidence intervals.

Table 5
Model Results for Moderated Mediation of Depression on HF HRV via Self-control, by Age

Variables	*b*	S.E.	*p*-value	Std. β	CI lower	CI upper
Depression on						
HF HRV	-0.005	0.003	0.073	-0.001	-0.010	0.001
Age	-0.005	0.003	0.073	-0.012	-0.010	0.001
Age*HF HRV	-0.005	0.003	0.073	-0.070	-0.010	0.001
Self-control	1.051	0.446	0.018	0.113	0.295	2.021
Self-control on						
HF HRV	0.019	0.104	0.856	0.045	-0.300	0.124
Age	-0.004	0.010	0.697	-0.088	-0.036	0.004
Age*HF HRV	0.000	0.002	0.856	0.049	-0.002	0.007
Indirect Effect						
Low Age	0.034	0.039	-	0.021	-0.028	0.131
High Age	0.045	0.041	-	0.032	-0.009	0.156

Note. S.E. refers to the standard error, Std. β refers to the standardized beta CI refers to the asymmetric confidence intervals.

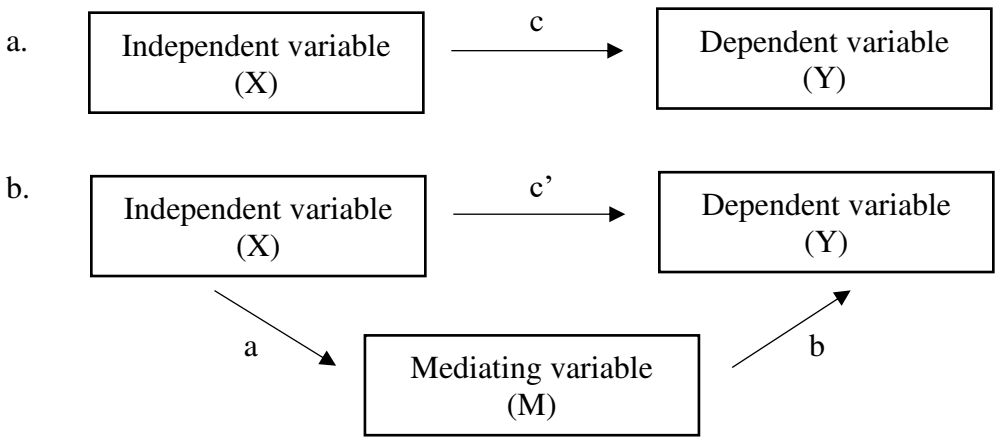

Figure 1. Conceptualization of path models with and without mediating variables. The individual variables and paths between them are labeled according to standard naming conventions.

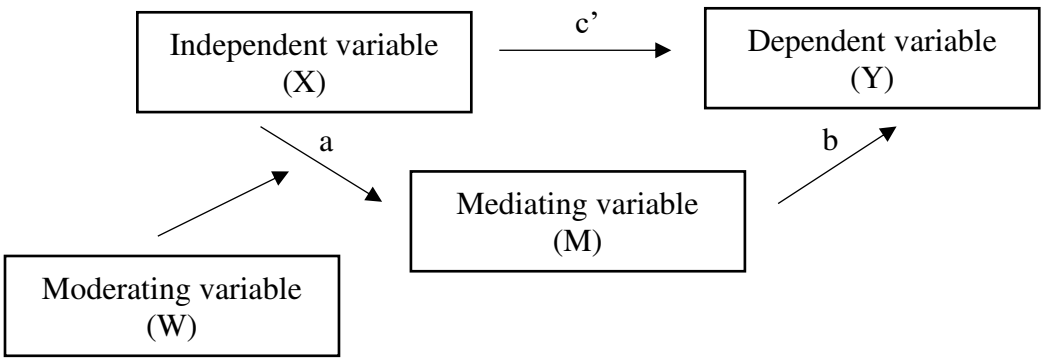

Figure 2. Conceptualization of the moderated mediation path model tested in the current study. The individual variables and paths between them are labeled according to standard naming conventions.

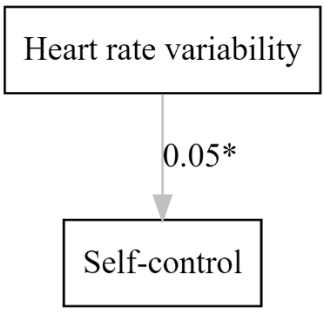

Figure 3. Model Results for Self-control on HF HRV. The numerical value in the figure corresponds to the unstandardized coefficient of the path. Results indicate that there was a significant relationship between HF HRV and SCS scores (r=.107, 95% ACI [0.006, 0.085]). * indicates $p < .05$.

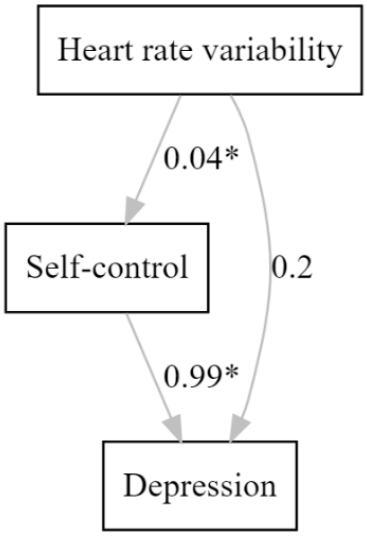

Figure 4. Model Results for HF HRV Relating to Depression via Self-control. The numerical values in the figure correspond to the unstandardized coefficients of the paths. Results indicate that self-control fully mediates the effect of HF HRV on depression as evidenced by the products of the *c'* path (*r*=.051, 95% ACI [-0.218, 0.538]), *a* path = (*r*=.104, 95% ACI [0.004, 0.087]), *b* path (*r*=.106, 95% ACI [0.137, 1.942]) and the indirect effects (*b*=0.043, *r*=.011, 95% ACI [0.003, 0.118]).]). * indicates $p < .05$.

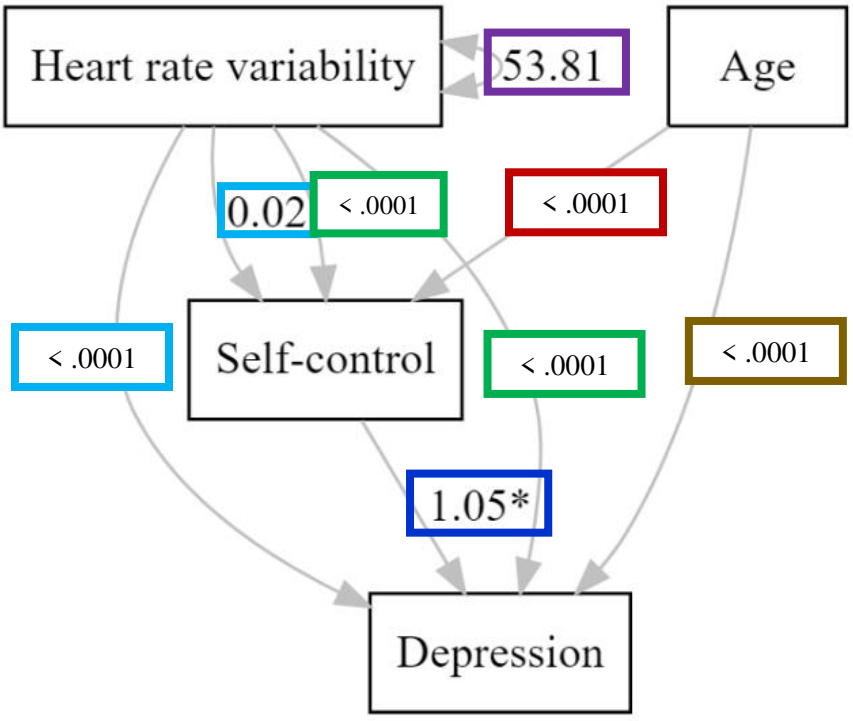

Figure 5. Model Results for Moderated Mediation of Depression on HF HRV via Self-control, by Age. The values highlighted in blue and green are the resulting regression coefficients from testing the moderating effect of age at 1 SD above and below the mean. The regression coefficient highlighted in red is the relationship between age and SC. The value highlighted in purple is the covariance of HRV, or the variance within the HRV variable. For the last 2 coefficients in the figure, the one highlighted in dark blue is the relationship between SC and dep, while the gold value is the relationship between age and depression. * indicates $p < .05$.

REFERENCES

Ahern, G. L., Sollers, J. J., Lane, R. D., Labiner, D. M., Herring, A. M., Weinand, M. E., Hutzler, R., & Thayer, J. F. (2001). Heart rate and heart rate variability changes in the intracarotid sodium amobarbital test. Epilepsia, 42(7), 912–921. https://doi.org/10.1046/j.1528-1157.2001.042007912.x

Aldao, A., Nolen-Hoeksema, S., & Schweizer, S. (2010). Emotion-regulation strategies across psychopathology: A meta-analytic review. Clinical psychology review, 30(2), 217–237. https://doi.org/10.1016/j.cpr.2009.11.004

Allen, B., Jennings, J. R., Gianaros, P. J., Thayer, J. F., & Manuck, S. B. (2015). Resting high-frequency heart rate variability is related to resting brain perfusion. Psychophysiology, 52(2), 277–287. https://doi.org/10.1111/psyp.12321

Almeida-Santos, M. A., Barreto-Filho, J. A., Oliveira, J. L., Reis, F. P., da Cunha Oliveira, C. C., & Sousa, A. C. (2016). Aging, heart rate variability and patterns of autonomic regulation of the heart. Archives of gerontology and geriatrics, 63, 1–8. https://doi.org/10.1016/j.archger.2015.11.011

Amat, J., Paul, E., Watkins, L. R., & Maier, S. F. (2008). Activation of the ventral medial prefrontal cortex during an uncontrollable stressor reproduces both the immediate and long-term protective effects of behavioral control. Neuroscience, 154(4), 1178–1186. https://doi.org/10.1016/j.neuroscience.2008.04.005

American Psychiatric Association. (2013). Diagnostic and statistical manual of mental disorders (5th ed.). https://doi.org/10.1176/appi.books.9780890425596

American Psychological Association. (2021). American Psychological Association (APA). American Psychological Association. https://www.apa.org/.

Appelhans, B. M., & Luecken, L. J. (2006). Heart rate variability as an index of regulated emotional responding. Review of General Psychology, 10(3), 229-240. https://doi.org/10.1037/1089-2680.10.3.229

Assari, S., & Lankarani, M. M. (2016). Association Between Stressful Life Events and Depression; Intersection of Race and Gender. Journal of racial and ethnic health disparities, 3(2), 349–356. https://doi.org/10.1007/s40615-015-0160-5

Bailey, R. K., Mokonogho, J., & Kumar, A. (2019). Racial and ethnic differences in depression: current perspectives. Neuropsychiatric disease and treatment, 15, 603–609. https://doi.org/10.2147/NDT.S128584

Baron, R. M., & Kenny, D. A. (1986). The moderator–mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. Journal of Personality and Social Psychology, 5, 1173–1182. https://doi.org/10.1037/0022-3514.51.6.1173

Bartra, O., McGuire, J. T., Kable, J. W. (2013). The valuation system: A coordinate-based meta-analysis of BOLD fMRI experiments examining neural correlates of subjective value. NeuroImage, 76, 412–427. doi:10.1016/j.neuroimage.2013.02.063

Bassett, D., Bear, N., Nutt, D., Hood, S., Bassett, S., & Hans, D. (2016). Reduced heart rate variability in remitted bipolar disorder and recurrent depression. The Australian and New Zealand journal of psychiatry, 50(8), 793–804. doi.org/10.1177/0004867416652734

Bauer, I. M., & Baumeister, R. F. (2011). Self-regulatory strength. In K. D. Vohs & R. F. Baumeister (Eds.), Handbook of self-regulation: Research, theory and, applications (2nd ed., pp. 64–82). New York, NY: Guilford Press.

Baumeister, R. F., & Heatherton, T. F. (1996). Self-Regulation Failure: An Overview. Psychological Inquiry, 7(1), 1–15. doi:10.1207/s15327965pli0701_1

Baumeister, R. F., & Vohs, K. D. (2003). Self-regulation and the executive function of the self. In M. R. Lear & J. P. Tangney (Eds.), Handbook of self and identity (pp. 197–217). New York, NY: Guilford Press

Baumeister, R. F., Bratslavsky, E., Muraven, M., & Tice, D. M. (1998). Ego depletion: Is the active self a limited resource? Journal of Personality and Social Psychology, 74(5), 1252–1265. doi:10.1037/0022-3514.74.5.1252

Baumeister, R. F., Heatherton, T. F., & Tice, D. M. (1994). Losing control: How and why people fail at self-regulation. Academic Press.

Baumgartner, T., Knoch, D., Hotz, P., Eisenegger, C., & Fehr, E. (2011). Dorsolateral and ventromedial prefrontal cortex orchestrate normative choice. Nat Neurosci, 14, 1468–1474, doi:10.1038/nn.2933, pmid:21964488.

Beaman, A. L., Klentz, B., Diener, E., & Svanum, S. (1979). Self-awareness and transgression in children: Two field studies. Journal of Personality and Social Psychology, 37(10), 1835–1846. https://doi.org/10.1037/0022-3514.37.10.1835

Beauchaine T. P. (2001). Vagal tone, development, and Gray's motivational theory: toward an integrated model of autonomic nervous system functioning in psychopathology. Dev. Psychopathology. 13, 183–214 10.1017/S0954579401002012

Beauchaine T. P. (2015). Respiratory Sinus Arrhythmia: A Transdiagnostic Biomarker of Emotion Dysregulation and Psychopathology. Current opinion in psychology, 3, 43–47. https://doi.org/10.1016/j.copsyc.2015.01.017

Beauchaine, T. P., & McNulty, T. (2013). Comorbidities and continuities as ontogenic processes: toward a developmental spectrum model of externalizing psychopathology. Development and psychopathology, 25(4 Pt 2), 1505–1528. doi.org/10.1017/S0954579413000746

Beauchaine, T. P., & Thayer, J. F. (2015). Heart rate variability as a transdiagnostic biomarker of psychopathology. International journal of psychophysiology: official journal of the International Organization of Psychophysiology, 98(2 Pt 2), 338–350. https://doi.org/10.1016/j.ijpsycho.2015.08.004

Benarroch E. E. (1993). The central autonomic network: functional organization, dysfunction, and perspective. Mayo Clinic proceedings, 68(10), 988–1001. https://doi.org/10.1016/s0025-6196(12)62272-1

Benoit, R. G., Szpunar, K. K., Schacter, D. L. (2014). Ventromedial prefrontal cortex supports affective future simulation by integrating distributed knowledge. Proceedings of the National Academy of Sciences, 111, 16550–16555. doi:10.1073/pnas.1419274111

Berkman, E. T., Hutcherson, C. A., Livingston, J. L., Kahn, L. E., Inzlicht, M. (2017). Self-control as value-based choice. Current Directions in Psychological Science, 26, 422–428. doi:10.1177/0963721417704394

Bigger, J. T. Jr., Albrecht, P., Steinman, R. C., Rolnitzky, L. M., Fleiss, J. L., and Cohen, R. J. (1989). Comparison of time- and frequency domain-based measures of cardiac parasympathetic activity in Holter recordings after myocardial infarction. Am. J. Cardiol. 64, 536–538.

Blankson, A. N., O'Brien, M., Leerkes, E M., Marcovitch, S., & Calkins, S. D. (2012). Differentiating processes of control and understanding in the early development of emotion and cognition. Social Development, 21, 1-20, 10.1111/j.1467-9507.2011.00593.x

Bray, S., Shimojo, S., O'Doherty, J. P. (2010). Human medial orbitofrontal cortex is recruited during experience of imagined and real rewards. Journal of Neurophysiology, 103, 2506–2512. doi:10.1152/jn.01030.2009

Brehm, J. W., & Self, E. A. (1989). The intensity of motivation. Annual Review of Psychology, 40, 109–131. https://doi.org/10.1146/annurev.ps.40.020189.000545

Brinkman, K., & Franzen, J. (2015). Depression and self-regulation: a motivational analysis and insights from effort-related cardiovascular reactivity. In Handbook of Biobehavioral Approaches to Self-Regulation, ed. GHD Gendolla, pp. 333–48. New York: Springer

Brown, L., Karmakar, C., Gray, R., Jindal, R., Lim, T., & Bryant, C. (2018). Heart rate variability alterations in late life depression: a meta-analysis. Journal of Affective Disorders, 235, 456–66. doi: 10.1016/j.jad.2018.04.071

Buccelletti, E., Gilardi, E., Scaini, E., Galiuto, L., Persiani, R., Biondi, A., Basile, F., & Silveri, N. G. (2009). Heart rate variability and myocardial infarction: systematic literature review and metanalysis. European review for medical and pharmacological sciences, 13(4), 299–307.

Buch, A.M., Liston, C. Dissecting diagnostic heterogeneity in depression by integrating neuroimaging and genetics. Neuropsychopharmacology. 46, 156–175 (2021). https://doi.org/10.1038/s41386-020-00789-3

Buchanan, T. W., Driscoll, D., Mowrer, S. M., Sollers, J. J., Thayer, J. F., Kirschbaum, C., & Tranel, D. (2010). Medial prefrontal cortex damage affects physiological and psychological stress responses differently in men and women. Psychoneuroendocrinology, 35(1), 56-66. doi.org/10.1016/j.psyneuen.2009.09.006

Buhle, J. T., Silvers, J. A., Wager, T. D., Lopez, R., Onyemekwu, C., Kober, H., Weber, J., & Ochsner, K. N. (2014). Cognitive reappraisal of emotion: a meta-analysis of human neuroimaging studies. Cerebral Cortex, 24(11), 2981–2990. https://doi.org/10.1093/cercor/bht154

Bush, G., Luu, P., & Posner, M. I. (2000). Cognitive and emotional influences in anterior cingulate cortex. Trends in cognitive sciences, 4(6), 215–222. https://doi.org/10.1016/s1364-6613(00)01483-2

Cannon, W. B. (1929). Organization for Physiological Homeostasis. Physiological Reviews, 9(3), 399-431. https://doi.org/10.1152/physrev.1929.9.3.399

Capuana, L. J., Dwyan, J., Tays, W. J., Elmers, J. L., Witherspoon, R., & Segalowitz, S. (2014).

Carnevali, L., Thayer, J. F., Brosschot, J. F., & Ottaviani, C. (2018). Heart rate variability mediates the link between rumination and depressive symptoms: a longitudinal study.

Carver, C. S., & Scheier, M. F. (1980). The self-attention-induced feedback loop and social facilitation. Journal of Experimental Social Psychology, 17, 545-568.

Carver, C. S., & Scheier, M. F. (1981). Attention and self-regulation: A control-theory approach to human behavior. New York, NY: Springer-Verlag.

Carver, C. S., & Scheier, M. F. (1998). On the self-regulation of behavior. Cambridge University Press. https://doi.org/10.1017/CBO9781139174794

Carver, C. S., & Scheier, M. F. (2011). Self-regulation of action and affect. In K. D. Vohs & R. F. Baumeister (Eds.), Handbook of self-regulation: Research, theory and, applications (2nd ed., pp. 3–21). New York, NY: The Guilford Press.

Chamorro, J., Bernardi, S., Potenza, M. N., Grant, J. E., Marsh, R., Wang, S., & Blanco, C. (2012). Impulsivity in the general population: a national study. Journal of Psychiatric Research, 46(8), 994–1001. https://doi.org/10.1016/j.jpsychires.2012.04.023

Cho, H. C. (2016). Age is just a number: frailty better evaluates age-dependent heart rhythm defects. Journal of Physiology, 594(23), 6805-6805. https://doi.org/10.1113/JP273370

Coccaro, E. F., Sripada, C. S., Yanowitch, R. N., & Phan, K. L. (2011). Corticolimbic function in impulsive aggressive behavior. Biological psychiatry, 69(12), 1153–1159. https://doi.org/10.1016/j.biopsych.2011.02.032

Cohen, J. (1988). Statistical Power Analysis for the Behavioral Sciences (2nd ed.). Hillsdale, NJ: Lawrence Erlbaum Associates, Publishers.

Connell, L. E. (2015). Applications of two-method measurement to explore associations between self-control and physical activity (Doctoral dissertation). https://etda.libraries.psu.edu/files/final_submissions/11370

Corr, P.J. & McNaughton, N. (2015). Neural mechanisms of low trait anxiety and risk for externalizing behavior. In: Beauchaine, T.P., Hinshaw, S.P. (Eds.), Oxford Handbook of Externalizing Spectrum Disorders. Oxford University Press, New York.

Coyne, J.C., & Gotlib, I.H. (1983). The role of cognition in depression: A critical appraisal. Psychological Bulletin, 94, 472–505.

Cuevas, K., & Bell, M. A. (2010). Developmental progression of looking and reaching performance on the A-not-B task. Developmental Psychology, 46, 1363-1371. 10.1037/a0020185

Cunningham W.A., Van Bavel J.J., & Johnsen I.R. (2008). Affective flexibility evaluative processing goals shape amygdala activity. Psychological Science, 19(2),152–60.

Davies, H. T., & Crombie, I. K. (2009). What are confidence intervals and p-values? Statistics, 2, 1-8.

DeBoer, R. W., Karemaker, J. M., & Strackee, J. (1984). Comparing spectra of a series of point events particularly for heart rate variability data. IEEE transactions on bio-medical engineering, 31(4), 384–387. https://doi.org/10.1109/TBME.1984.325351

Dehaene, S., Posner, M. I., & Tucker, D.M. (1994). Localization of a neural system for error detection and compensation. Psychological Science, 5(5), 303-305. https://doi.org/10.1111/j.1467-9280.1994.tb00630.x

Dell'Acqua, C., Bo, E. D., Benvenuti, S.M., & Palomba, D. (2020). Reduced heart rate variability is associated with vulnerability to depression. Journal of Affective Disorders Reports, 1. https://doi.org/10.1016/j.jadr.2020.100006

DeYoung, C. G. (2011). Impulsivity as a personality trait. In K. D. Vohs & R. F. Baumeister (Eds.), Handbook of self-regulation: Research, theory and, applications (2nd ed.). New York, NY: Guilford Press

Dienberg Love, G., Seeman, T. E., Weinstein, M., & Ryff, C. D. (2010). Bioindicators in the MIDUS national study: protocol, measures, sample, and comparative context. Journal of aging and health, 22(8), 1059–1080. https://doi.org/10.1177/0898264310374355

Drabant, E. M., McRae, K., Manuck, S. B., Hariri, A. R., & Gross, J. J. (2009). Individual differences in typical reappraisal use predict amygdala and prefrontal responses. Biological psychiatry, 65(5), 367–373. https://doi.org/10.1016/j.biopsych.2008.09.007

Drayer, R. A., Mulsant, B. H., Lenze, E. J., Rollman, B. L., Dew, M. A., Kelleher, K., Karp, J. F., Begley, A., Schulberg, H. C., & Reynolds, C. F., 3rd (2005). Somatic symptoms of depression in elderly patients with medical comorbidities. International journal of geriatric psychiatry, 20(10), 973–982. https://doi.org/10.1002/gps.1389

Duckworth, A. L., & Kern, M. L. (2011). A Meta-Analysis of the Convergent Validity of Self-Control Measures. Journal of Research in Personality, 45(3), 259–268. doi:10.1016/j.jrp.2011.02.004

Duckworth, A.L., & Seligman, M.E.P. (2005). Self-discipline outdoes IQ in predicting academic performance of adolescents. Psychological Science, 16, 939–944.

Duckworth, A.L., Tsukayama, E., & May, H. (2010). Establishing causality using longitudinal hierarchical linear modeling: An illustration predicting achievement from self-control. Social Psychology and Personality Science, 1, 311–317.

Edwards, J. R. (2012). *Mediation* [PDF document]. Retrieved from Lecture Notes Online Website: http://public.kenan-flagler.unc.edu/faculty/edwardsj/MEDIATE.NOT.pdf

Edwards, J. R., & Lambert, L. S. (2007). Methods for integrating moderation and mediation: a general analytical framework using moderated path analysis. Psychological methods, 12(1), 1–22. https://doi.org/10.1037/1082-989X.12.1.1

Efron, B., & Tibshirani, R. (1986). Bootstrap Methods for Standard Errors, Confidence Intervals, and Other Measures of Statistical Accuracy. Statistical Science, 1(1), 54 – 75. https://doi.org/10.1214/ss/1177013815

Eippert, F., Veit, R., Weiskopf, N., Erb, M., Birbaumer, & Anders, S. (2007). Regulation of emotional responses elicited by threat-related stimuli. Human Brain Mapping, 28(5), 409-423. https://doi.org/10.1002/hbm.20291

Elenkov, I. J., Wilder, R. L., Chrousos, G. P., & Vizi, E. S. (2000). The sympathetic nerve--an integrative interface between two supersystems: the brain and the immune system. Pharmacological reviews, 52(4), 595–638.

Etkin, A., & Wager, T. D. (2007). Functional neuroimaging of anxiety: a meta-analysis of emotional processing in PTSD, social anxiety disorder, and specific phobia. The American journal of psychiatry, 164(10), 1476–1488. https://doi.org/10.1176/appi.ajp.2007.07030504

Factors influencing the role of cardiac autonomic regulation in the service of cognitive control. Biological Psychology, 102, 88-97. 10.1016/j.biopsycho.2014.07.015

Friederich, H., Schild, S., Schellberg, D., & Quenter, A. (2006). Cardiac parasympathetic regulation in obese women with binge eating disorder. International Journal of Obesity, 30(3), 534-542. doi: 10.1038/sj.ijo.0803181

Fukusaki, C., Kawakubo, K., & Yamamoto, Y. (2000). Assessment of the primary effect of aging on heart rate variability in humans. Clinical Autonomic Research, 10(3), 123-130. doi:10.1007/BF02278016

Gabella, G. (2012). Autonomic nervous system. Neuroscience, https://doi.org/10.1002/9780470015902.a0000081.pub2

Garnefski, N., & Kraaij, V. (2007). The cognitive emotion regulation questionnaire. European Journal of Psychological Assessment, 23, 141-149. 10.1027/1015-5759.23.3.141

Gendolla, G.H. E. (2000). On the impact of mood on behavior: An integrative theory and review. Review of General Psychology, 4(4), 378-408. https://doi.org/10.1037/1089-2680.4.4.378

Gentzler, A.L., Santucci, A. K., Kovacs, M., & Fox, N. A. (2009). Respiratory sinus arrhythmia reactivity predicts emotion regulation and depressive symptoms in at-risk and control children. Biological Psychology, 82, 156-163. 10.1016/j.biopsycho.2009.07.002

Goldberger A. L. (1991). Is the normal heartbeat chaotic or homeostatic? News in physiological sciences, 6, 87–91. https://doi.org/10.1152/physiologyonline.1991.6.2.87

Gray, J. A. (1982). The Neuropsychology of Anxiety: An Enquiry into the Functions of the Septo-hippocampal System. Oxford University Press, New York.

Gray, J. A. (1987). The Psychology of Fear and Stress. Cambridge University Press, New York.

Greenwood P. M. (2007). Functional plasticity in cognitive aging: review and hypothesis. Neuropsychology, 21(6), 657–673. https://doi.org/10.1037/0894-4105.21.6.657

Gross, J. J., & John, O. P. (2003). Individual differences in two emotion regulation processes: Implications for affect, relationships, and well-being. Journal of Personality and Social Psychology, 85(2), 348–362. https://doi.org/10.1037/0022-3514.85.2.348

Gyurak, A., & Ayduk, O. (2008). Resting respiratory sinus arrhythmia buffers against rejection sensitivity via emotion control. Emotion, 8, 458-467, 10.1037/1528-3542.8.4.458

Hafeman, D. M. (2009). “Proportion Explained”: A Causal Interpretation for Standard Measures of Indirect Effect? American Journal of Epidemiology, 170(11), 1443–1448. https://doi.org/10.1093/aje/kwp283

Hainsworth R. (1995). The control and physiological importance of heart rate, in Heart Rate Variability, eds Malik M., Camm A. J. (Armonk, NY: Futura Publishing Company, Inc.), 3–19.

Hansen, A. L., Johnsen, B. H., & Thayer, J. F. (2003). Vagal influence on working memory and attention. International Journal of Psychophysiology, 48(3), 263–274. https://doi.org/10.1016/s0167-8760(03)00073-4

Harris, A., Hare, T., & Randel, A. (2013). Temporally dissociable mechanisms of self-control: Early attentional filtering versus late value modulation. Journal of Neuroscience, 33(48), 18917-18931. https://doi.org/10.1523/JNEUROSCI.5816-12.2013

Harris, F. J. (1978). On the use of windows for harmonic analysis with the discrete Fourier transform. Proceedings of the IEEE, 66(1), 51-83.

Hartmann, R., Schmidt, F. M., Sander, C., & Hegerl, U. (2019). Heart rate variability as indicator of clinical state in depression. Frontiers in Psychiatry, 9, 735. 10.3389/fpsyt.2018.00735

Hayes, A. F. (2015) An Index and Test of Linear Moderated Mediation. Multivariate Behavioral Research, 50(1), 1-22, https://doi.org/10.1080/00273171.2014.962683

Hayes, A. F., & Rockwood, N. J. (2020). Conditional process analysis: Concepts, computation, and advances in the modeling of the contingencies of mechanisms. American Behavioral Scientist, 64(1), 19–54. https://doi.org/10.1177/0002764219859633

Heatherton T. F. (2011). Neuroscience of self and self-regulation. Annual review of psychology, 62, 363–390. https://doi.org/10.1146/annurev.psych.121208.131616

Heatherton, T. F., & Wagner, D. D. (2011). Cognitive neuroscience of self-regulation failure. Trends in Cognitive Sciences, 15, 132–139. doi:10.1016/j.tics.2010.12.005

Hilgarter K., Schmid-Zalaudek, K., Csanady-Leitner, R., Mortl, M., Rossler, A., Lackner, H.K. (2021). Phasic heart rate variability and the association with cognitive performance: A cross-sectional study in a healthy population setting. PLoS ONE, 16(3), e0246968. https://doi.org/10.1371/journal.pone.0246968

Hill, L. K., Hu, D. D., Koenig, J., Sollers, J. J., 3rd, Kapuku, G., Wang, X., Snieder, H., & Thayer, J. F. (2015). Ethnic differences in resting heart rate variability: a systematic review and meta-analysis. Psychosomatic medicine, 77(1), 16–25. https://doi.org/10.1097/PSY.0000000000000133

Hofmann, W., Friese, M., & Strack, F. (2009). Impulse and self-control from dual-systems perspective. Perspectives on Psychological Science, 4, 162–176.

Holland, P. C., & Gallagher, M. (2004). Amygdala-frontal interactions and reward expectancy. Current opinion in neurobiology, 14(2), 148–155. doi.org/10.1016/j.conb.2004.03.007

Holzman, J. B., & Bridgett, D. J. (2017). Heart rate variability indices as bio-markers of top-down self-regulatory mechanisms: A meta-analytic review. Neuroscience and biobehavioral reviews, 74(Pt A), 233–255. doi.org/10.1016/j.neubiorev.2016.12.032

Hoyle, R. H. (1995). The structural equation modeling approach: Basic concepts and fundamental issues. In R. H. Hoyle (Ed.), Structural equation modeling: Concepts, issues, and applications (pp. 1–15). Sage Publications, Inc.

Hoyle, R.H., & Gallagher, P. (2015). The interplay of personality and self-regulation. In APA Handbook of Personality and Social Psychology, Vol. 4, Personality Processes and Individual Differences, ed. M Mikulincer, PR Shaver, ML Cooper, RJ Larsen, pp. 189–207. Washington, DC: Am. Psychol. Assoc.

Hughes, D. C., Blazer, D. G., & George, L. K. (1988). Age differences in life events: a multivariate controlled analysis. International journal of aging & human development, 27(3), 207–220. https://doi.org/10.2190/F9RP-8V9D-CGH7-2F0N

Huikuri, H. V., Makikallio, T. H., & Perkiomaki, J. (2003). Measurement of heart rate variability by methods based in nonlinear dynamics. Journal of Electrocardiology, 36(1), 95-99. https://doi.org/10.1016/j.jelectrocard.2003.09.021

Ingjaldsson, J. T., Laberg, J. C., & Thayer, J. F. (2003). Reduced heart rate variability in chronic alcohol abuse: relationship with negative mood, chronic thought suppression, and compulsive drinking. Biological psychiatry, 54(12), 1427–1436. https://doi.org/10.1016/s0006-3223(02)01926-1

Jänig W. (1989) Autonomic Nervous System. In: Schmidt R.F., Thews G. (eds) Human Physiology. Springer, Berlin, Heidelberg. https://doi.org/10.1007/978-3-642-73831-9_16

Jarczok, M.N., Kleber, M.E., Koenig, J., Loerbroks, A., Herr, R.M., Hoffmann, K., Fischer, J. E., Benyamini, Y., & Thayer, J. F. (2015). Investigating the associations of self-rated health: Heart rate variability is more strongly associated than inflammatory and other frequently used biomarkers in a cross-sectional occupational sample. PLoS ONE, 10(2): e0117196. https://doi.org/10.1371/journal.pone.0117196

Jazwinski, S. M., & Kim, S. (2019). Examination of the Dimensions of Biological Age. Frontiers in genetics, 10, 263. https://doi.org/10.3389/fgene.2019.00263

Jennings, J.R., Yovetich, N. (1991). Autonomic nervous system Indices. In Jennings, J.R., Coles, M.G.H. (Eds.), Handbook of Cognitive Psychophysiology: Central and Autonomic Nervous System Approaches (pp. 706–728) Chichester: Wiley.

Joormann, J., & Siemer, M. (2011). Affective processing and emotional regulation in dysphoria and depression: Cognitive biases and deficits in cognitive control. Social and Personality Compass, 5(1), 13-28. https://doi.org/10.1111/j.1751-9004.2010.00335.x

Jose, P. E. (2016). The merits of using longitudinal mediation. *Educational Psychologist, 51*(3-4), 331-341.

Karemaker J. M. (2017). An introduction into autonomic nervous function. Physiological measurement, 38(5), R89–R118. https://doi.org/10.1088/1361-6579/aa6782

Kemp, AH, Koenig, J and Thayer, JF (2017) From psychological moments to mortality: a multidisciplinary synthesis on heart rate variability spanning the continuum of time. Neuroscience & Biobehavioral Reviews 83, 547–567.

Kemp, A. H., & Quintana, D. S. (2013). The relationship between mental and physical health: insights from the study of heart rate variability. International Journal of Psychophysiology, 89(3), 288–296. https://doi.org/10.1016/j.ijpsycho.2013.06.018

Kemp, A. H., Quintana, D. S., Felmingham, K. L., Matthews, S., & Jelinek, H. F. (2012). Depression, comorbid anxiety disorders, and heart rate variability in physically healthy, unmedicated patients: implications for cardiovascular risk. PloS one, 7(2), e30777. https://doi.org/10.1371/journal.pone.0030777

Khan, S., & Khan, R. A. (2017). Chronic stress leads to anxiety and depression. Annals of Psychiatry and Mental Health, 5(1), 1091-1094.

Kluttig, A., Schumann, B., Swenne, C. A., Kors, J. A., Kuss, O., Schmidt, H., Werdan, K., Haerting, J., & Greiser, K. H. (2010). Association of health behaviour with heart rate variability: a population-based study. BMC cardiovascular disorders, 10, 58. https://doi.org/10.1186/1471-2261-10-58

Koch, C., Wilhelm, M., Salzmann, S., Rief, W., & Euteneuer, R. (2019). A meta-analysis of heart rate variability in major depression. Psychological Medicine, 49, 1948-1957. 10.1017/S0033291719001351

Koenig, J., Kemp, A.H., Beauchaine, T.P., Thayer, J.F., & Kaess, M. (2016). Depression and resting state heart rate variability in children and adolescents—A systematic review and meta-analysis. Clinical Psychology Reviews, 46, 136–150. doi:10.1016/j.cpr.2016.04.013

Kohn, N., Eickhoff, S. B., Scheller, M., Laird, A. R., Fox, P. T., & Habel, U. (2014). Neural network of cognitive emotion regulation--an ALE meta-analysis and MACM analysis. NeuroImage, 87, 345–355. https://doi.org/10.1016/j.neuroimage.2013.11.001

Koster, E. H., De Lissnyder, E., Derakshan, N., & De Raedt, R. (2011). Understanding depressive rumination from a cognitive science perspective: the impaired disengagement hypothesis. Clinical Psychology Review, 31(1), 138–145. https://doi.org/10.1016/j.cpr.2010.08.005

Kronke, K., Wolff, M., Mohr, H., Kraplin, A., Smolka, M. N., Buhringer, G., Goschke, T. (2020). Predicting real-life self-control from brain activity encoding the value of anticipated future outcomes. Psychological Science, 31(3), 268-279. https://doi-org.ezproxy2.library.colostate.edu/10.1177/0956797619896357

Kukanova, B., & Mravec, B. (2006). Complex intracardiac nervous system. Bratislavske lekarske listy, 107(3), 45–51.

Kumral, D., Schaare, H. L., Beyer, F., Reinelt, J., Uhlig, M., Liem, F., Lampe, L., Babayan, A., Reiter, A., Erbey, M., Roebbig, J., Loeffler, M., Schroeter, M. L., Husser, D. M., Witte, A. V. Villringer, A., & Gaebler, M. (2019). The age-dependent relationship between resting heart rate variability and functional brain connectivity. Neuroimage, 185(15), 521-533. https://doi.org/10.1016/j.neuroimage.2018.10.027

Krueger R. F. (1999). The structure of common mental disorders. Archives of general psychiatry, 56(10), 921–926. https://doi.org/10.1001/archpsyc.56.10.921

Laakso, A., Wallius, E., Kajander, J., Bergman, J., Eskola, O., Solin, O., Ilonen, T., Salokangas, R. K., Syvälahti, E., & Hietala, J. (2003). Personality traits and striatal dopamine synthesis capacity in healthy subjects. The American journal of psychiatry, 160(5), 904–910. https://doi.org/10.1176/appi.ajp.160.5.904

Lane, R. D., Weidenbacher, H., Smith, R., Fort, C., Thayer, J. F., & Allen, J. J. (2013). Subgenual anterior cingulate cortex activity covariation with cardiac vagal control is altered in depression. Journal of affective disorders, 150(2), 565–570. https://doi.org/10.1016/j.jad.2013.02.005

LeDoux, J. E. (1996). The emotional brain: The mysterious underpinnings of emotional life. Simon & Schuster.

Lee, I. M., Shiroma, E. J., Lobelo, F., Puska, P., Blair, S. N., Katzmarzyk, P. T., & Lancet Physical Activity Series Working Group (2012). Effect of physical inactivity on major non-communicable diseases worldwide: An analysis of burden of disease and life expectancy. Lancet, 380(9838), 219–229. doi.org/10.1016/S0140-6736(12)61031-9

Lewinsohn, P. M., Seeley, J. R., Roberts, R. E., & Allen, N. B. (1997). Center for Epidemiologic Studies Depression Scale (CES-D) as a screening instrument for depression among community-residing older adults. Psychology and aging, 12(2), 277–287. https://doi.org/10.1037//0882-7974.12.2.277

Maier, S. F., Amat, J., Baratta, M. V., Paul, E., & Watkins, L. R. (2006). Behavioral control, the medial prefrontal cortex, and resilience. Dialogues in clinical neuroscience, 8(4), 397–406. https://doi.org/10.31887/DCNS.2006.8.4/smaier

Markandmedia.nl. (2012). Finapres Medical Systems: Home. Finapres Medical Systems | Home. https://www.finapres.com/.

Markus, H. R., & Kitayama, S. (1991). Culture and the self: Implications for cognition, emotion, and motivation. Psychological Review, 98(2), 224–253. https://doi.org/10.1037/0033-295X.98.2.224

Mayeux R. (2004). Biomarkers: potential uses and limitations. NeuroRx: The Journal of the American Society for Experimental NeuroTherapeutics, 1(2), 182–188. https://doi.org/10.1602/neurorx.1.2.182

Mazure, C. M. (1998). Life stressors as risk factors in depression. Clinical Psychology: Science and Practice, 5(3), 291–313. https://doi.org/10.1111/j.1468-2850.1998.tb00151.x

McEwen B. S. (1998). Stress, adaptation, and disease. Allostasis and allostatic load. Annals of the New York Academy of Sciences, 840, 33–44. https://doi.org/10.1111/j.1749-6632.1998.tb09546.x

McEwen, B.S., & Wingfield, J. C. (2003). The concept of allostasis in biology and biomedicine. Hormones and Behavior, 43(1), 2–15. https://doi.org/10.1016/S0018-506X(02)00024-7

Metcalfe, J., & Mischel, W. (1999). A hot/cool-system analysis of delay of gratification: dynamics of willpower. Psychological Review, 106(1), 3–19.

Meyer, G.J., Finn, S.E., Eyde, L.D., Kay, G.G., Moreland, K.L., Dies, R.R., & Reed, G.M. (2001). Psychological testing and psychological assessment: A review of evidence and issues. American Psychologist, 56, 128–165.

Mezzacappa, E., Kindlon, D., Saul, J. P., & Earls, F. (1998). Executive and motivational control of performance task behavior, and autonomic heart-rate regulation in children: Physiologic validation of two-factor solution inhibitory control. Journal of Child Psychology and Psychiatry, 39(4), 525–531. doi.org/10.1017/S0021963098002273

Milad, M. R., & Quirk, G. J. (2002). Neurons in medial prefrontal cortex signal memory for fear extinction. Nature, 420(6911), 70–74. https://doi.org/10.1038/nature01138

Miller, E.K. (2000). The prefrontal cortex: No simple matter. Neuroimage, 2, 447–450.

Mischel, W., & Ayduk, O. (2011). Willpower in a cognitive-affective processying system: The dynamics of delay of gratification. In K. D. Vohs & R. F. Baumeister (Eds.), Handbook of self-regulation: Research, theory and, applications (2nd ed., pp. 83–105). New York, NY: Guilford Press.

Mischel, W., Shoda, Y., & Rodriguez, M.L. (1989). Delay of gratification in children. Science, 244, 933–938.

Miyake, A., Friedman, N.P., Emerson, M.J., Witzki, A.H., & Howerter, A. (2000). The unity and diversity of executive functions and their contributions to complex "frontal lobe" tasks: A latent variable analysis. Cognitive Psychology, 41, 49–100.

Moffitt, T. E., Arseneault, L., Belsky, D., Dickson, N., Hancox, R. J., Harrington, H., Houts, R., Poulton, R., Roberts, B. W., Ross, S., Sears, M. R., Thomson, W. M., & Caspi, A. (2011). A gradient of childhood self-control predicts health, wealth, and public safety. Proceedings of the National Academy of Sciences of the United States of America, 108(7), 2693–2698. https://doi.org/10.1073/pnas.1010076108

Moghtadaei, M., Jansen, H. J., Mackasy, M., Rafferty, S. A., Bogachev, O., Sapp, J. L., Howlett, S. E., & Rose, R. A. (2016). The impacts of age and frailty on heart rate and sinoatrial node function. Journal of Physiology, 594(23), 7105-7126. doi.org/10.1113/JP272979

Morawetz, C., Alexandrowicz, R. W., & Heekeren, H. R. (2017). Successful emotion regulation is predicted by amygdala activity and aspects of personality: A latent variable approach. Emotion, 17(3), 421–441. https://doi.org/10.1037/emo0000215

Muraven, M., & Baumeister, R. F. (2000). Self-regulation and depletion of limited resources: Does self-control resemble a muscle? Psychological Bulletin, 126(2), 247–259. doi:10.1037/0033-2909.126.2.247

Muraven, M., Baumeister, R. F., & Tice, D. M. (1999). Longitudinal improvement of self-regulation through practice: building self-control strength through repeated exercise. Journal of Social Psychology, 139(4), 446–457. doi:10.1080/00224549909598404

Myung, I. J. (2003). Tutorial on maximum likelihood estimation. Journal of Mathematical Psychology, 47(1), 90–100. https://doi.org/10.1016/S0022-2496(02)00028-7

National Institute of Mental Health. (2018). National Institute of Mental Health (NIMH). National Institute of Mental Health. https://www.nimh.nih.gov/.

National Institute of Mental Health. (2019). National Institute of Mental Health (NIMH). National Institute of Mental Health. https://www.nimh.nih.gov/.

Naylor S. (2003). Biomarkers: current perspectives and future prospects. Expert Review of Molecular Diagnostics, 3(5), 525–529. https://doi.org/10.1586/14737159.3.5.525

Neuhaus, E. & Beauchaine, T.P. (2013). Impulsivity and vulnerability to psychopathology. In: Beauchaine, T.P., Hinshaw, S.P. (Eds.), Child and Adolescent Psychopathology, 2nd ed. Wiley, Hoboken, NJ, pp. 197–226.

Newman, J.P., Kosson, D.S., & Patterson, C.M. (1992). Delay of gratification in psychopathic and nonpsychopathic offenders. Journal of Abnormal Psychology, 101, 630–636.

Newsom. (2020). *Missing Data and Missing Data Estimation in SEM* [PDF document]. Retrieved from Lecture Notes Online Website: http://web.pdx.edu/~newsomj/semclass/ho_missing.pdf

Oaten, M., & Cheng, K. (2006). Longitudinal gains in self-regulation from regular physical exercise. British Journal of Health Psychology, 11, 717–733. doi:10.1348/135910706X96481

Ochsner, K. N., Silvers, J. A., & Buhle, J. T. (2012). Functional imaging studies of emotion regulation: a synthetic review and evolving model of the cognitive control of emotion. Annals of the New York Academy of Sciences, 1251, E1–E24. https://doi.org/10.1111/j.1749-6632.2012.06751.x

Ogletree-Hughes, M. L., Stull, L. B., Sweet, W. E., Smedira, N. G., McCarthy, P. M., & Moravec, C. S. (2001). Mechanical unloading restores beta-adrenergic responsiveness and reverses receptor downregulation in the failing human heart. Circulation, 104(8), 881–886. https://doi.org/10.1161/hc3301.094911

Opitz, P. C., Rauch, L. C., Terry, D. P., & Urry, H. L. (2012). Prefrontal mediation of age differences in cognitive reappraisal. Neurobiological Aging, 33, 645-655. 10.1016/j.neurobiolaging.2010.06.004

Opthof, T. (2000). The normal range and determinants of the intrinsic heart rate in man. Cardiovascular research, 45(1), 177–184. doi.org/10.1016/s0008-6363(99)00322-3

Pang, K. C., & Beauchaine, T. P. (2013). Longitudinal patterns of autonomic nervous system responding to emotion evocation among children with conduct problems and/or depression. Developmental psychobiology, 55(7), 698–706. https://doi.org/10.1002/dev.21065

Park, G., Vasey, M. W., Van Bavel, J. J., & Thayer, J. F. (2014). When tonic cardiac vagal tone predicts changes in phasic vagal tone: the role of fear and perceptual load. Psychophysiology, 51(5), 419–426. https://doi.org/10.1111/psyp.12186

Paton, J., Belova, M., Morrison, S. et al. The primate amygdala represents the positive and negative value of visual stimuli during learning. Nature, 439, 865–870. https://doi.org/10.1038/nature04490

Porges, S. W. (1996). Physiological regulation in high-risk infants: A model for assessment and potential intervention. Development and Psychopathology, 8(1), 29–42. https://doi.org/10.1017/S0954579400006969

Potenza, M. N., & de Wit, H. (2010). Control yourself: alcohol and impulsivity. Alcoholism, clinical and experimental research, 34(8), 1303–1305. https://doi.org/10.1111/j.1530-0277.2010.01214.x

R Core Team (2020) R: A Language and Environment for Statistical Computing. R Foundation for Statistical Computing, Vienna. - References - Scientific Research Publishing. https://www.scirp.org/(S(lz5mqp453edsnp55rrgjct55))/reference/ReferencesPapers.aspx?ReferenceID=2342186.

Radloff, L. S. (1977). The CES-D Scale: A self-report depression scale for research in the general population. Applied Psychological Measurement, 1(3), 385-401. https://doi.org/10.1177/014662167700100306

RenuMadhavi, C.H., & Ananth, A.G. (2012). A review of heart rate variability and its association with diseases. International Journal of Software and Computer Engineering, 2, 2231–2307.

Reyes del Paso, G. A., Langewitz, W., Mulder, L. J., van Roon, A., & Duschek, S. (2013). The utility of low frequency heart rate variability as an index of sympathetic cardiac tone: a review with emphasis on a reanalysis of previous studies. Psychophysiology, 50(5), 477–487. https://doi.org/10.1111/psyp.12027

Reynard, A., Gevirtz, R., Berlow, R., Brown, M., & Boutelle, K. (2011). Heart rate variability as a marker of self-regulation. Applied Psychophysiology and Biofeedback, 36(3), 209–215. https://doi.org/10.1007/s10484-011-9162-1

Reynolds, B., Ortengren, A., Richards, J. B., & de Wit, H. (2006). Dimensions of impulsive behavior: Personality and behavioral measures. Personality and Individual Differences, 40(2), 305–315. https://doi.org/10.1016/j.paid.2005.03.024

Rigdon, E. E., Schumacker, R. E., & Wothke, W. (1998). A comparative review of interaction and nonlinear modeling. In R. E. Schumacker & G. A. Marcoulides (Eds.), Interaction and nonlinear effects in structural equation modeling (pp. 1–16). Lawrence Erlbaum Associates Publishers.

Roberts, S. O., Bareket-Shavit, C., Dollins, F. A., Goldie, P. D., & Mortenson, E. (2020). Racial Inequality in Psychological Research: Trends of the Past and Recommendations for the Future. Perspectives on psychological science: a journal of the Association for Psychological Science, 15(6), 1295–1309. https://doi.org/10.1177/1745691620927709

Rodriguez, M. L., Mischel, W., & Shoda, Y. (1989). Cognitive person variables in the delay of gratification of older children at risk. Journal of Personality and Social Psychology, 57(2), 358–367. doi:10.1037/0022-3514.57.2.358

Rosseel, Y. (2012). lavaan: An R Package for Structural Equation Modeling. Journal of Statistical Software, 48(2), 1-36. https://doi.org/10.18637/jss.v048.i02

Roth, D.L., Ackerman, M. L., Okonkwo, O. C., & Burgio, L. D. (2008). The four-factor model of depressive symptoms in dementia caregivers: A structural equation model of ethnic differences. Psychology and Aging, 23, 567–576.

Ruscio, A.M., Seitchik, A.E., Gentes, E.L., Jones, J.D., & Hallion, L.S. (2011). Perseverative thought: a robust predictor of response to emotional challenge in generalized anxiety disorder and major depressive disorder. Behaviour Research and Therapy 49, 867–74.

Ryu, E., & Cheong, J. (2017). Comparing Indirect Effects in Different Groups in Single-Group and Multi-Group Structural Equation Models. Frontiers in psychology, 8, 747. https://doi.org/10.3389/fpsyg.2017.00747

Sakaki, M., Yoo, H. J., Nga, L., Lee, T. H., Thayer, J. F., & Mather, M. (2016). Heart rate variability is associated with amygdala functional connectivity with MPFC across younger and older adults. Neuroimage, 139, 44-52, 10.1016/j.neuroimage.2016.05.076

Sandercock, G. R. H., Hardy-Shepherd, D., Nunan, D. & Brodie, D. (2008). The relationships between self-assessed habitual physical activity and noninvasive measures of cardiac autonomic modulation in young healthy volunteers. Journal of Sports Science, 26(11), 1171-1177.

Santens, E., Claes, L., Dierckx, E. & Dom, G. (2020). Effortful Control – A transdiagnostic dimension underlying internalizing and externalizing psychopathology. Neuropsychobiology, 79(4-5), 255-269.

Santucci, A. K., Silk, J. S., Shaw, D. S., Gentzler, A., Fox, N. A., & Kovacs, M. (2008). Vagal tone and temperament as predictors of emotion regulation strategies in young children. Developmental Psychobiology, 50, 2015-2016, 10.1002/dev.20283

Sauder, C. L., Beauchaine, T. P., Gatzke-Kopp, L. M., Shannon, K. E., & Aylward, E. (2012). Neuroanatomical correlates of heterotypic comorbidity in externalizing male adolescents. Journal of Clinical Child and Adolescent Psychology, 41(3), 346–352. https://doi.org/10.1080/15374416.2012.658612

Scheier, M. F., Fenigstein, A., & Buss, A. H. (1974). Self-awareness and physical aggression. Journal of Experimental Social Psychology, 10(3), 264–273. https://doi.org/10.1016/0022-1031(74)90072-9

Schmeichel, B. J., & Vohs, K. (2009). Self-affirmation and self-control: Affirming core values counteracts ego depletion. Journal of Personality and Social Psychology, 96(4), 770–782. https://doi.org/10.1037/a0014635

Schroeder, S. A. (2007). We can do better – Improving the health of the American people. New England Journal of Medicine, 357, 1221-1228. Doi: 10.1056/NEJMsa073350

Schuster, A., K., Jarczok, M. N., Fischer, J. E., & Thayer, J. F. (2014). Retinal vessel analysis and heart rate variability. International Journal of Cardiology, 176(3), 1268-1269. https://doi.org/10.1016/j.ijcard.2014.07.190

Segerstrom, S. C., & Nes, L. S. (2007). Heart Rate Variability Reflects Self-Regulatory Strength, Effort, and Fatigue. Psychological Science, 18(3), 275–281. doi:10.1111/j.1467-9280.2007.01888.x

Selig, J. P. & Preacher, K. J. (2009). Mediation models for longitudinal data in developmental research. *Research in Human Development, 6*(2-4), 144-164.

Shaffer, F., & Ginsberg, J.P. (2017). An overview of heart rate variability metrics and norms. Frontiers in Public Health, 5, 258. https://doi.org/10.3389/fpubh.2017.00258

Shaffer, F., McCraty, R., & Zerr, C. L. (2014). A healthy heart is not a metronome: an integrative review of the heart's anatomy and heart rate variability. Frontiers in psychology, 5, 1040. https://doi.org/10.3389/fpsyg.2014.01040

Shaffer, F., Meehan, Z. M., & Zerr, C. L. (2020). A Critical Review of Ultra-Short-Term Heart Rate Variability Norms Research. Frontiers in neuroscience, 14, 594880. https://doi.org/10.3389/fnins.2020.594880

Smith, R., Allen, J. J., Thayer, J. F., & Lane, R. D. (2015). Altered functional connectivity between medial prefrontal cortex and the inferior brainstem in major depression during appraisal of subjective emotional responses: A preliminary study. Biological psychology, 108, 13–24. https://doi.org/10.1016/j.biopsycho.2015.03.007

Smith, R., Allen, J. J., Thayer, J. F., Fort, C., & Lane, R. D. (2014). Increased association over time between regional frontal lobe BOLD change magnitude and cardiac vagal control with sertraline treatment for major depression. Psychiatry research, 224(3), 225–233. https://doi.org/10.1016/j.pscychresns.2014.08.015

Sowell, E. R., Thompson, P. M., & Toga, A. W. (2004). Mapping changes in the human cortex throughout the span of life. Neuroscientist, 10, 372-392, 10.1177/1073858404263960

Sternini C. (1997). Organization of the peripheral nervous system: autonomic and sensory ganglia. The journal of investigative dermatology. Symposium proceedings, 2(1), 1–7. https://doi.org/10.1038/jidsymp.1997.2

Stetson, B. A., Rahn, J. M., Dubbert, P. M., Wilner, B. I., & Mercury, M. G. (1997). Prospective evaluation of the effects of stress on exercise adherence in community-residing women. Health Psychology, 16(6), 515–520. doi:10.1037/0278-6133.16.6.515

Strauman, T. J. (2017). Self-regulation and psychopathology: Toward and Integrative Translational Research Paradigm. Annual Review of Clinical Psychology, 13, 497-523. doi: 10.1146/annurev-clinpsy-032816-045012

Strauman, T.J. (1992). Self-guides, autobiographical memory, and anxiety and dysphoria: toward a cognitive model of vulnerability to emotional distress. Journal of Abnormal Psychology, 101, 87–95.

Stroud, C. B., Davila, J., & Moyer, A. (2008). The relationship between stress and depression in the first onsets versus recurrences: a meta-analytic review. Journal of Abnormal Psychology, 117, 206-213.

Sturge-Apple, M. L., Suor, J. H., Davies, P. T., Cicchetti, D., Skibo, M. A., & Rogosch, F. A. (2016). Vagal tone and children's delay of gratification differential sensitivity in resource-Poor and resource-Rich environments. Psychological Science, 27(6), 885-893. 10.1177/0956797616640269

Sullivan, G. M., & Feinn, R. (2012). Using Effect Size-or Why the P Value Is Not Enough. Journal of graduate medical education, 4(3), 279–282. https://doi.org/10.4300/JGME-D-12-00156.1

Tangney, J. P., Baumeister, R. F., & Boone, A. L. (2004). High self-control predicts good adjustment, less pathology, better grades, and interpersonal success. Journal of Personality, 72(2), 271–324.

Task Force of the European Society of Cardiology and the North American Society of Pacing and Electrophysiology. (1996). Heart rate variability: standards of measurement, physiological interpretation and clinical use. Circulation, 93(5), 1043–1065.

Tennant C. (2002). Life events, stress and depression: a review of recent findings. The Australian and New Zealand journal of psychiatry, 36(2), 173–182. https://doi.org/10.1046/j.1440-1614.2002.01007.x

Thayer, J. F., & Lane, R. D. (2009). Claude Bernard and the heart-brain connection: further elaboration of a model of neurovisceral integration. Neuroscience and biobehavioral reviews, 33(2), 81–88. https://doi.org/10.1016/j.neubiorev.2008.08.004

Thayer, J. F., & Siegle, G. J. (2002). Neurovisceral integration in cardiac and emotional regulation. Engineering in Medicine & Biology, 21(4), 24–29. https://doi.org/10.1109/memb.2002.1032635

Thayer, J. F., Ahs, F., Fredrikson, M., Sollers, J. J., 3rd, & Wager, T. D. (2012). A meta-analysis of heart rate variability and neuroimaging studies: implications for heart rate variability as a marker of stress and health. Neuroscience and biobehavioral reviews, 36(2), 747–756. https://doi.org/10.1016/j.neubiorev.2011.11.009

Thayer, J. F., Hansen, A. L., Saus-Rose, E., & Johnsen, B. H. (2009). Heart rate variability, prefrontal neural function, and cognitive performance: the neurovisceral integration perspective on self-regulation, adaptation, and health. Annals of behavioral medicine: a publication of the Society of Behavioral Medicine, 37(2), 141–153. https://doi.org/10.1007/s12160-009-9101-z

Thayer, J. F., Yamamoto, S. S., & Brosschot, J. F. (2010). The relationship of autonomic imbalance, heart rate variability and cardiovascular disease risk factors. International journal of cardiology, 141(2), 122–131. https://doi.org/10.1016/j.ijcard.2009.09.543

Thayer, J.F., & Lane, R.D. (2000). A model of neurovisceral integration in emotion regulation and dysregulation. Journal of Affective Disorders, 61, 201–216.

Thayer, J.F., & Sternberg, E. (2006). Beyond heart rate variability. Annals of the New York Academy of Sciences, 1088, 361–372. doi: 10.1196/annals.1366.014.

Tice, D. M., Baumeister, R. F., Shmueli, D., & Muraven, M. (2007). Restoring the self: Positive affect helps improve self-regulation following ego depletion. Journal of Experimental Social Psychology, 43(3), 379–384. doi:10.1016/j.jesp.2006.05.007

Tortora G. J., & Derrickson B. H. (2014). Principles of Anatomy and Physiology. Hoboken, NJ: John Wiley & Sons, Inc

Tsuji, H., Venditti, F. J., Jr, Manders, E. S., Evans, J. C., Larson, M. G., Feldman, C. L., & Levy, D. (1994). Reduced heart rate variability and mortality risk in an elderly cohort. The Framingham Heart Study. Circulation, 90(2), 878–883. doi.org/10.1161/01.cir.90.2.878

Tyler, J. M., & Burns, K. C. (2008). After Depletion: The Replenishment of the Self's Regulatory Resources. Self and Identity, 7(3), 305–321. doi:10.1080/15298860701799997

Tyson, P.D. (1998). Physiological arousal, reactive aggression, and the induction of an incompatible relaxation response. Aggression and Violent Behavior, 3(2), 143-158. https://doi.org/10.1016/S1359-1789(97)00002-5

U.S. Department of Health and Human Services. (2017). Midlife in the United States. National Institute on Aging. https://www.nia.nih.gov/research/resource/midlife-united-states.

Umetani, K., Singer, D. H., McCraty, R., & Atkinson, M. (1998). Twenty-four-hour time domain heart rate variability and heart rate: relations to age and gender over nine decades. Journal of the American College of Cardiology, 31(3), 593–601. https://doi.org/10.1016/s0735-1097(97)00554-8

Urry, H. L., van Reekum, C. M., Johnstone, T., Kalin, N. H., Thurow, M. E., Schaefer, H. S., Jackson, C. A., Frye, C. J., Greischar, L. L., Alexander, A. L., & Davidson, R. J. (2006). Amygdala and ventromedial prefrontal cortex are inversely coupled during regulation of negative affect and predict the diurnal pattern of cortisol secretion among older adults.

Journal of Neuroscience, 26(16), 4415–4425. https://doi.org/10.1523/JNEUROSCI.3215-05.2006

Vaillancourt, D. E., & Newell, K. M. (2002). Changing complexity in human behavior and physiology through aging and disease. Neurobiology of aging, 23(1), 1–11. https://doi.org/10.1016/s0197-4580(01)00247-0

van Veen, V., & Carter, C. S. (2002). The anterior cingulate as a conflict monitor: fMRI and ERP studies. Physiology & behavior, 77(4-5), 477–482. https://doi.org/10.1016/s0031-9384(02)00930-7

Vargas Pelaez, A. F., Gao, Z., Ahmad, T. A., Leuenberger, U. A., Proctor, D. N., Maman, S. R., & Muller, M. D. (2016). Effect of adrenergic agonists on coronary blood flow: a laboratory study in healthy volunteers. Physiological reports, 4(10), e12806. https://doi.org/10.14814/phy2.12806

Vasudev, A., O'Brien, J. T., Tan, M. P., Parry, S. W., & Thomas, A. J. (2011). A study of orthostatic hypotension, heart rate variability and baroreflex sensitivity in late-life depression. Journal of affective disorders, 131(1-3), 374–378. https://doi.org/10.1016/j.jad.2010.11.001

Verkerk, A. O., Remme, C. A., Schumacher, C. A., Scicluna, B. P., Wolswinkel, R., de Jonge, B., Bezzina, C. R., & Veldkamp, M. W. (2012). Functional Nav1.8 channels in intracardiac neurons: the link between SCN10A and cardiac electrophysiology. Circulation research, 111(3), 333–343. doi.org/10.1161/CIRCRESAHA.112.274035

Voss, A., Schroeder, R., Heitmann, A., Peters, A., & Perz, S. (2015). Short-Term Heart Rate Variability- Influence of Gender and Age in Healthy Subjects. PLoS ONE 10(3): e0118308. https://doi.org/10.1371/journal.pone.0118308

Voss, A., Schulz, S., Schroeder, R., Baumert, M., & Caminal, P. (2009). Methods derived from nonlinear dynamics for analyzing heart rate variability. Philosophical transactions. Series A, Mathematical, physical, and engineering sciences, 367(1887), 277–296. https://doi.org/10.1098/rsta.2008.0232

Waxenbaum, J. A., Reddy, V., & Varacallo, M. (2020). Anatomy, Autonomic Nervous System. In StatPearls. StatPearls Publishing.

Wegener, D. T., & Fabrigar, L. R. (2000). Analysis and desgin for nonexperimental data: Addressing causal and noncausal hypothesis. In H. T. Reis & C. M. Judd (Eds.), Handbook of research methods in social and personality psychology (pp. 412–450). Cambridge University Press.

Whalen, P. J., & Phelps, E. A. (Eds.). (2009). The human amygdala. The Guilford Press.

Williams, P.J., & Thayer, J.F. (2009). Executive functioning and health: Introduction to the special series. Annals of Behavioral Medicine, 37, 101–105.

Winkelmann, T., Thayer, J. F., Pohlack, S., Nees, F., Grimm, O., & Flor, H. (2017). Structural brain correlates of heart rate variability in a healthy young adult population. Brain Structure and Function, 222, 1061-1068. doi: 10.1007/s00429-016-1185-1

Wong, M. L., & Licinio, J. (2001). Research and treatment approaches to depression. Nature reviews. Neuroscience, 2(5), 343–351. https://doi.org/10.1038/35072566

World Health Organization. (2020). World Health Organization (WHO). World Health Organization. https://www.who.int/.

Wright, A. G., Krueger, R. F., Hobbs, M. J., Markon, K. E., Eaton, N. R., & Slade, T. (2013). The structure of psychopathology: toward an expanded quantitative empirical model. Journal of abnormal psychology, 122(1), 281–294. https://doi.org/10.1037/a0030133

Yamasaki, H., LaBar, K. S., & McCarthy, G. (2002). Dissociable prefrontal brain systems for attention and emotion. Proceedings of the National Academy of Sciences of the United States of America, 99(17), 11447–11451. https://doi.org/10.1073/pnas.182176499

Yang, L., Zhao, Y., Wang, Y., Liu, L., Zhang, X., Li, B., & Cui, R. (2015). The Effects of Psychological Stress on Depression. Current neuropharmacology, 13(4), 494–504. https://doi.org/10.2174/1570159x1304150831150507

Yoo, H. J., Thayer, J. F., Greening, S., Lee, T., Ponzio, A., Min, J., Sakaki, M., Nga, M. M., & Koenig, J. (2018). Brain structural concomitants of resting state heart rate variability in the young and old: evidence from two independent samples. Brain Structure and Function, 223, 727–737 https://doi.org/10.1007/s00429-017-1519-7

Young, H. A., & Benton, D. (2018). Heart-rate variability: a biomarker to study the influence of nutrition on physiological and psychological health? Behavioural pharmacology, 29(2 and 3-Spec Issue), 140–151. https://doi.org/10.1097/FBP.0000000000000383

Zeki Al Hazzouri, A., Haan, M. N., Deng, Y., Neuhaus, J., & Yaffe, K. (2014). Reduced heart rate variability is associated with worse cognitive performance in elderly Mexican Americans. Hypertension, 63(1), 181–187. https://doi.org/10.1161/HYPERTENSIONAHA.113.01888

Zulfiqar, U., Jurivich, D. A., Gao, W., & Singer, D. H. (2010). Relation of high heart rate variability to healthy longevity. The American journal of cardiology, 105(8), 1181–1185. https://doi.org/10.1016/j.amjcard.2009.12.022

APPENDIX A

Self-report Measures

Self-administered Questionnaire

Note: Selected relevant questions that will be included in analyses are listed.

What is your date of birth?

Have you ever had any of the following conditions/illnesses? – Heart disease

Have you ever had any of the following conditions/illnesses? – High blood pressure

Have you ever had any of the following conditions/illnesses? – Circulation problems

Have you ever had any of the following conditions/illnesses? – Blood clots

Have you ever had any of the following conditions/illnesses? – Heart murmur

Have you ever had a diagnosis of any of the following medical conditions? – Heart failure

Have you ever had a diagnosis of any of the following medical conditions? – Irregular heartbeat

Have you ever had a heart attack?

Do you have a pacemaker?

Have you ever had any of the following conditions/illnesses? – TIA (Transient Ischemic Attack or "mini stroke," where a person has temporary symptoms of a stroke that pass quickly).

Do you have a personal history of any of the following medical conditions? - Stroke

Have you ever had any of the following conditions/illnesses? – Diabetes

Have you ever had any of the following conditions/illnesses? – Hypothyroidism

Have you ever had any of the following conditions/illnesses? – Epilepsy

Do you have a personal history of any of the following medical conditions? – Serious head injury

Have you ever had a diagnosis of any of the following conditions/illnesses? – Schizophrenia

Have you ever had a diagnosis of any of the following medical conditions? – Post-traumatic stress disorder

Have you ever had a diagnosis of any of the following medical conditions? – Bipolar disorder

Self-control Scale (SCS)

Note: "R" indicates item is reverse coded before constructing the scale score.

The following questions are about your views of yourself. Please circle the number that corresponds to how much you agree or disagree with the following statements.

1. "I can make myself do things I don't want to do."

2. "When something bad happens to me, I think of all the others who are much worse off than I am."

3. "I can control my thoughts and desires if I need to."

4. "It is important to me to be able to think, feel, and act differently depending on the needs and demands of the situation."

5. "One can be a better person only through changing one's thoughts and feelings."

6. "It is important for me to be strong in body and mind."

7. "I control my emotions by changing the way I think about the situation I'm in."

8. "I keep my emotions to myself."

9. "When I'm faced with a stressful situation, I make myself think about it in a way that helps me stay calm."

10. "When I am feeling negative emotions (such as sadness or anger), I make sure not to express them."

11. "I am known as an emotional person." (R)

12. "It is important to me that I not bother others."

13. “I try to behave so as not to cause trouble to others.”

14. “I sometimes worry that I am a burden on others.”

15. “I know my own limitations.”

16. “I do my best to maintain a calm mind.”

17. “A top priority in my life is to do well what I am supposed to do.”

18. “I feel very tense when I am being evaluated by others.”

19. “I am often concerned about how other people might respond to me.”

Center for Epidemiological Studies – Depression Scale (CES-D)

Note: “R” indicates item is reverse coded before constructing the scale score.

“During the past week…?”

1.” I was bothered by things that usually don’t bother me.”

2.” I did not feel like eating; my appetite was poor.”

3.” I felt that I could not shake off the blues even with the help of my family and friends.”

4.” I felt that I was just as good as other people.” (R)

5.” I had trouble keeping my mind on what I was doing.”

6. “I felt depressed.”

7.” I felt that everything I did was an effort.”

8.” I felt hopeful about the future.” (R)

9.” I thought my life had been a failure.”

10.” I felt fearful.”

11.” My sleep was restless.”

12.” I was happy.” (R)

13.” I talked less than usual.”

14.” I felt lonely.”

15.” People were unfriendly.”

16.” I enjoyed life.” (R)

17.” I had crying spells.”

18.” I felt sad.”

19.” I felt that people dislike me.”

20.” I could not get “going”.

Life Events Checklist

Check the appropriate boxes next to any of the following experiences you have had.

Ever repeated school year

Ever sent away from home

Ever had parent out of job

Ever parent drank caused problems

Ever parent drugs caused problems

Ever dropped out of school

Ever suspended/expelled from school

Ever flunked out of school

Ever fired from a job

Ever no job for long time

Ever parent died

Ever parents divorced

Ever spouse/partner engaged in infidelity

Ever child died

Ever sibling died

Ever significant in-law difficulties

Ever child experienced life-threatening

Ever lost home to fire/flood/etc

Ever physically assaulted

Ever sexually assaulted

Ever serious legal difficulties/prison

Ever jail detention

Ever bankruptcy declared

Ever financial loss unrelated to work

Ever welfare

Ever entered armed forces

Ever experienced combat

APPENDIX B

R Script Generated for Analyses

```
# ---Dissertation Analysis Script---
#
# This script performs the following statistical analyses:
#   Descriptive statistics
#   Bi-variate correlations
#   Hypothesis 1: Simple linear regression model
#   Hypothesis 2: Path model with lavaan package - mediation model
#   Hypothesis 3: Path model with lavaan package - moderated mediation model
#
# Marielle L. Darwin | August 26 2021 | Last update: Sept 19 2021

# Install packages
install.packages('lavaan')
install.packages('mediation')
install.packages('lme4')
install.packages('pastecs')
install.packages('ppcor')
install.packages('apaTables')
install.packages('psych')
install.packages('tidyverse')
install.packages('lavaanPlot')

# Load packages
library(lavaan)
library(mediation)
library(lme4)
library(pastecs)
library(ppcor)
library(apaTables)
library(psych)
library(tidyverse)
library(lavaanPlot)

# Clear workspace
rm(list = ls())

# Set working directory
setwd("C:/Users/darwinm/Documents/Dissertation/R stats/")

# Load data
data <- read.csv("FINALvariables.csv")

# Assign missing variables
data[data == 99] <- NA

##Descriptive statistics table------------------------

values <- cbind(data$LE_TOTAL, data$AGE, data$SCS_TOTAL, data$CESD_TOTAL,
                data$CESDnoSC, data$HRV)
options(scipen=100)  #Convert from sci notation
options(digits=2)    #2 decimal places
stat.desc(values)    #Display values
```

```r
##Bi-variate correlations ----------------------------

# Correlation matrix accounting for missing data
corFiml(data, covar = FALSE,show=FALSE)

# Output as table with M, SD, correlation value, and significance
apa.cor.table(data, show.conf.interval = TRUE)

##Hypothesis 1 ----------------------------------------
  # X = HRV
  # Y = SCS_TOTAL

fit1 <- sem('SCS_TOTAL ~ HRV', data = data,
              missing = 'fiml', fixed.x = F,
              se = "bootstrap",
              bootstrap = 1000)

# Display model output
summary(fit1, standardized=TRUE, fit.measures = TRUE)
parameterestimates(fit1,
  boot.ci.type = "bca.simple",
  level = .95, ci = TRUE,
  standardized = TRUE)

# SEM plot
labels <- list(HRV = "Heart rate variability", SCS_TOTAL = "Self-control")

lavaanPlot(model = fit1, labels = labels, node_options = list(shape = "box",
          fontname = "times"), edge_options = list(color = "grey"),
          coefs = TRUE, covs = TRUE, stars = "regress")

##Hypothesis 2 ----------------------------------------
  # X = HRV
  # M = SCS_TOTAL
  # Y = CESD_TOTAL

set.seed(050692)
X <- data$HRV
M <- data$SCS_TOTAL
Y <- data$CESD_TOTAL

# Mediation model
mediation.model <- data.frame(X = X, Y = Y, M = M)
model <- ' Y ~ c*X              # Direct effect
           M ~ a*X              # Mediator
           Y ~ b*M
           ab := a*b            # Indirect effect (a*b)
           total := c + (a*b)   # Total effect
         '
fit <- sem(model, data = mediation.model,
           missing = 'fiml', fixed.x = F,
           se = "bootstrap",
           bootstrap = 1000)

# Display model output
summary(fit,standardized=TRUE, fit.measures = TRUE)

parameterEstimates(fit,
                   boot.ci.type = "bca.simple",
                   level = .95, ci = TRUE,
                   standardized = TRUE)

# SEM plot
labelsMed <- list(X = "Heart rate variability", M = "Self-control",
               Y = "Depression")

lavaanPlot(model = fit, labels = labelsMed, node_options = list(shape = "box",
           fontname = "times"), edge_options = list(color = "grey"),
           coefs = TRUE, covs = TRUE, stars = "regress")
```

```r
##Hypothesis 3 ------------------------------------------
  # X = HRV
  # M = SCS_TOTAL
  # W = AGE
  # Y = CESD_TOTAL

# Mean center variables
center_scale <- function(x) {
  scale(x, scale = FALSE)
}

center_scale(data)

# Create interaction term
data$interact <- data$SCS_TOTAL*data$AGE

# Moderated mediation model
Mod.Med.Lavaan <-
  'SCS_TOTAL ~ a1*HRV + a2*AGE + a3*HRV:AGE
   CESD_TOTAL ~ c*HRV + c*AGE + c*HRV:AGE + b1*SCS_TOTAL

# Parameter estimate of mean of age
AGE ~ AGE.mean*1 #naming the parameter est of mean

# Parameter estimate of variance of age
AGE ~~ AGE.var*AGE #naming the parameter est of age

#Indirect effects conditional on moderator (a1 + a3*Modvalue)*b1
indirect.SDbelow := (a1 + a3*(AGE.mean-sqrt(AGE.var)))*b1
indirect.SDabove := (a1 + a3*(AGE.mean+sqrt(AGE.var)))*b1

#Direct effects conditional on moderator (cdash1 + cdash3*ModValue)
direct.SDbelow := c + c*(AGE.mean-sqrt(AGE.var))
direct.SDabove := c + c*(AGE.mean+sqrt(AGE.var))

#Total effects conditional on moderator
total.SDbelow := direct.SDbelow + indirect.SDbelow
total.SDabove := direct.SDabove + indirect.SDabove

#Proportion mediated conditional on moderator
#To match the output of "mediate" package
prop.mediated.SDbelow := indirect.SDbelow / total.SDbelow
prop.mediated.SDabove := indirect.SDabove / total.SDabove

#Index of moderated mediation
  #An alternative way of testing if conditional indirect effects are
  #significantly different from each other
index.mod.med := a3*b1
'

Mod.Med.SEM <- sem(model = Mod.Med.Lavaan,
                   data = data,
                   missing = 'fiml', fixed.x = F,
                   se = "bootstrap",
                   bootstrap = 1000)

# Display model output
summary(Mod.Med.SEM, standardized=TRUE, fit.measures = TRUE)

parameterEstimates(Mod.Med.SEM,
                   boot.ci.type = "bca.simple",
                   level = .95, ci = TRUE,
                   standardized = TRUE)

# SEM plot
labels <- list(HRV = "Heart rate variability", SCS_TOTAL = "Self-control",
               CESD_TOTAL = "Depression", AGE = "Age")

lavaanPlot(model = Mod.Med.SEM, labels = labels, node_options = list(shape =
           "box", fontname = "times"), edge_options = list(color = "grey"),
            coefs = TRUE, covs = TRUE, stars = "regress")
```

APPENDIX C

Analyses for CES-D Factors

The model for Hypotheses 2 was additionally tested in the same manner as stated in the Results, except with each CES-D subscale in place of the CES-D total score according to the four factor structure (Radloff, 1977). None of the models ran with the four subscales of the CES-D instead of a total score were statistically significant or had a notable effect size.

The CES-D Depressed Affect Subscale was not statistically significant *(c'* path = (*b*=0.063, *r*=.028, 95% ACI [-0.125, 0.252]), *a* path = (*b*=0.045, *r*=.106, 95% ACI [0.007, 0.087]), *b* path (*b*=-.119, *r*=-0.022, 95% ACI [-.566, 0.243]) and the indirect effects (*b*=-0.005, *r*=0.002, 95% ACI [-0.008, 0.005]).

The CES-D Positive Affect Subscale was not statistically significant *(c'* path = (*b*=-0.027, *r*=.014, 95% ACI [-0.192, 0.148]), *a* path = (*b*=0.045, *r*=.107, 95% ACI [0.008, 0.087]), *b* path (*b*=0.126, *r*=0.027, 95% ACI [0.488, 0.126]) and the indirect effects (*b*=-0.022, *r*=0.011, 95% ACI [-0.185, 0.156]).

The CES-D Somatic and Retarded Activity Subscale was not statistically significant *(c'* path = (*b*=0.071, *r*=.033, 95% ACI [-0.096, 0.274]), *a* path = (*b*=0.045, *r*=.106, 95% ACI [0.007, 0.086]), *b* path (*b*=-0.259, *r*=0.051, 95% ACI [-0.613, 0.097]) and the indirect effects (*b*=-0.012, *r*=0.028, 95% ACI [-0.108, 0.263]).

The CES-D Interpersonal Subscale was not statistically significant *(c'* path = (*b*=0.016, *r*=.023, 95% ACI [-0.044, 0.072]), *a* path = (*b*=0.045, *r*=.107, 95% ACI [0.008, 0.087]), *b* path (*b*=-0.019, *r*=-0.012, 95% ACI [-0.128, 0.089]) and the indirect effects (*b*=0.015, *r*=0.022, 95% ACI [-0.045, 0.071]).

APPENDIX D

Supplementary Analyses: Life Events and Depression Risk

Background and Methods

There is a strong association between negative life events and subsequent risk of depression (Tennant, 2002). The experience of these life events, such as difficulties in school or with parents, divorce, bankruptcy, death, or military combat, is both a short-term trigger and a long-term predictor for instances of depression, even twenty-five years after such events have occurred (Assari & Lankarani, 2016; Mazure, 1998). Furthermore, age is a significant factor that affects the quantity of experienced negative life events (Hughes, Blazer, & George, 1988). Supplementary analyses were performed to determine if the quantity of negative life events was associated with age and depression. The Life Event Checklist from the MIDUS database was employed to quantify the number of negative life events that were experienced by participants. This continuous variable was calculated by summing the total number of endorsements on the checklist. Bivariate correlations were performed to test the relationship between scores on the Life Event Checklist, HRV, and depression. It was expected that the quantity of experienced life events would be positively associated with both age and CES-D scores. The items included in this self-report measure are listed in Appendix A.

Results

Bivariate correlations were calculated to determine if the quantity of experienced negative life events was associated with age or depression. It was expected that the quantity of endorsed negative life events was positively associated with both age and CES-D scores. Results support this prediction in that there was a small positive association between endorsed negative

life events and age (r=.15, p<.01, CI [.06, .23]) and between endorsed negative life events and scores on the CES-D (r=.19, p<.01, CI [.11, .27]). Results are presented in Table 5.

Discussion

The supplementary analysis aimed to determine if the quantity of experienced negative life events was associated with age or depression. It was expected that the quantity of endorsed negative life events was positively associated with both age and CES-D scores. Results from bi-variate correlations support this prediction in that there was a small positive association between endorsed negative life events and age and between endorsed negative life events and scores on the CES-D.

The finding that depression was associated with increasing age may be linked to a rise in negative life events commonly experienced in older adulthood such as debilitating medical disorders, loss of loved ones, less control over activities of daily living, and an inability to partake in once-regular activities (American Psychological Association, 2021). These stressors, along with potentially less social support than in earlier years, may put one at heightened risk of experiencing depression and support the findings of the current analysis.

These results additionally provide an explanation of the influence of stress and the manifestation of depression as depicted in the literature. When faced with a potential threat, self-control-related abilities permit the individual to consider mitigating circumstances, or reappraise the situation, such as assigning meaning to ambiguous cues, assuming plausible implications, and employing strategies to adjust emotional value before reacting (Morawetz et al., 2017). When considering these variables during a decision to exert a behavioral response, PFC regions are engaged that enable the person to inhibit an automatic response to a perceived threat initiated by the amygdala.

These precarious dynamics point to the importance of healthy cognitive and emotional regulation in the face of stress. The CAPS theory of self-control in particular details how stress influences the interaction between cognitive and affective abilities that affect a person's capacity to exert self-control (Metcalfe & Mischel, 1999). The cognitive system is more likely to dominate goal-directed decision making in times of low or moderate stress and the influence of the emotional system increases as stress increases. The cognitive system would be most helpful in guiding decision-making during times of high stress, lending itself to an ironic situation in which self-control is most needed in times when it is the most difficult to access (Connell, 2015; Metcalfe & Mischel, 1999; Mischel & Ayduk, 2011). The results of the correlation analyses are supported by the CAPS theory of self-control in that stressful events often impede cognitive abilities, which may then negatively affect emotional regulation.