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Depressed Mood, Rumination, and Heart Rate Variability in At-Risk University Students

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Abstract

Background: Substantial evidence supports the association between rumination and depressive symptoms. Furthermore, autonomic dysregulation, as indexed by low levels of heart rate variability (HRV) is related to both maladaptive emotional regulation (e.g., rumination) and depressive symptoms.

Aim of the study: The purpose of this study was to investigate the interplay between heart rate variability, rumination, and depressive symptoms. Specifically, this study focused on the possible moderating role of heart rate variability in the association between rumination and depression.

Methods: 31 individuals took part in the study (10 males, 21 females). Self-report questionnaires were used to assess rumination and depressive symptoms (Ruminative Response Scale and Beck Depression Inventory-II, respectively). A time-domain measure of vagally mediated heart rate variability (rMSSD) was computed from short electrocardiogram recordings obtained through a smartphone-based photoelectric volumetric pulse wave assay.

Results and conclusions: The findings of this study indicate that both rumination and vagally mediated HRV (as measured by rMSSD) are significantly associated with depressive symptoms. Specifically, those with greater rumination and those with lower heart rate variability exhibited higher levels of depressive symptoms. Additionally, the results demonstrate that the association between rumination and depression is moderated by heart rate variability: among individuals with greater rumination, those with reduced HRV had higher levels of depression. These findings highlight the complex interplay between autonomic dysregulation and cognitive dysfunctions involved in depressive symptoms. The study suggests the importance of considering both cognitive-affective (i.e., rumination) and autonomic (HRV) factors to improve the understanding of depression and develop targeted interventions for its management. Limitations of this study include its cross-sectional design, which restricts causal inferences and the assessment of predictive relationships, and the potential limitations introduced by conducting the study remotely, suggesting the need for future longitudinal research and replication in controlled laboratory settings.

Keywords: Rumination, Depression, HRV.

PART I

CHAPTER 1

DEPRESSIVE SYMPTOMS AND RUMINATION

1.1 Depression

Depression has been defined as the second most prevalent mental health disease in the world for the past three decades (Dattani, 2021). Almost 280 million individuals were diagnosed with a depressive disorder in 2019, describing 3,67% of the global population (Institute of Health Metrics and Evaluation, 2019). Depression causes a considerable functional impairment, similarly to severe chronic medical conditions, including diabetes and congestive heart failure (Hays et al., 1995). A meta-review conducted by Chesney et al. (2014) found that suicidal mortality is 10 times greater in the depressed population than in the general population. Moreover, the economic effects of depression are substantial: the estimate of the total annual cost of depression in Europe in 2004 amounted to €118 billion (Sobocki et al., 2006), and the estimated incremental economic burden of adults with Major Depressive Disorder (MDD) in the U.S. increased by 37.9% from $236.6 billion to $326.2 billion between 2010 and 2018 (Greenberg et al., 2021). The tremendous functional, societal, and economic burden of depression highlights the need to address depression in terms of early identification and prevention.

1.1.1 Definition and Classification

Depression is characterized by persistent feelings of sadness, hopelessness, and a lack of interest or pleasure in once-enjoyable activities (World Health Organization [WHO], 2023). The fifth edition of the Diagnostic and Statistical Manual of Mental Disorders, Text Revision (DSM-5-TR; American Psychiatric Association, 2022) describes eight different types of depressive disorders: disruptive mood dysregulation disorder, major depressive disorder (including major depressive episode), persistent depressive disorder, premenstrual dysphoric disorder, substance/medication-induced depressive disorder, depressive disorder due to another medical condition, other specified depressive disorder, and the unspecified depressive disorder. The differential diagnosis among depressive disorders depends on symptoms onset, duration, and presumed aetiology: for example, major depressive disorder lasts at least two weeks, while persistent depressive disorder is a chronic condition that persists for at least two years (American Psychiatric Association, 2022).

According to the DSM-5-TR, Major Depressive Disorder (MDD) is the most prevalent among depressive disorders (American Psychiatric Association, 2022). Particularly, diagnostic criteria for MDD include affective (e.g., sadness and loss of interest or pleasure), cognitive (e.g., loss of concentration and slowness of thought), and somatic (e.g., loss or gain of weight and fatigue) symptoms.

1.1.2 Subclinical Symptoms as Depression Risk Factors

The development of depression is influenced by the complex interplay of several risk factors. Dobson and Dozois (2011) divided such factors into three main domains (Figure 1.1): (a) biological factors, (b) cognitive factors, and (c) social factors.

- *Biological factors* include genetics, hormones, and neurotransmitters. Research has shown that depression tends to run in families, suggesting a genetic component (Dobson & Dozois, 2011). Additionally, imbalances in hormones such as cortisol and serotonin have been linked to depression (Tafet et al., 2001). Similarly, changes in the levels of neurotransmitters such as dopamine and norepinephrine can contribute to depression as well (Nutt et al., 2006). Overall, these biological factors can play a significant role in the development of depression.
- *Cognitive factors* and emotional-cognitive interference such as negative thinking patterns and low self-esteem can contribute to the onset of depressive symptoms (Dobson & Dozois, 2011). Research has shown that individuals who tend to engage in negative self-talk and rumination are more likely to develop depression. Additionally, those with low self-esteem may be more susceptible to negative life events, which can trigger depressive symptoms.
- *Social factors* including stress, limited social support, and adverse life events can all contribute to depression (Dobson & Dozois, 2011). High levels of stress are associated with depression, and individuals lacking social support may be more susceptible to depression when facing stressful life events. Traumatic experiences like abuse or loss can also lead to depressive symptoms. Social support and other forms of social connection serve as protective factors, reducing the risk of depression.

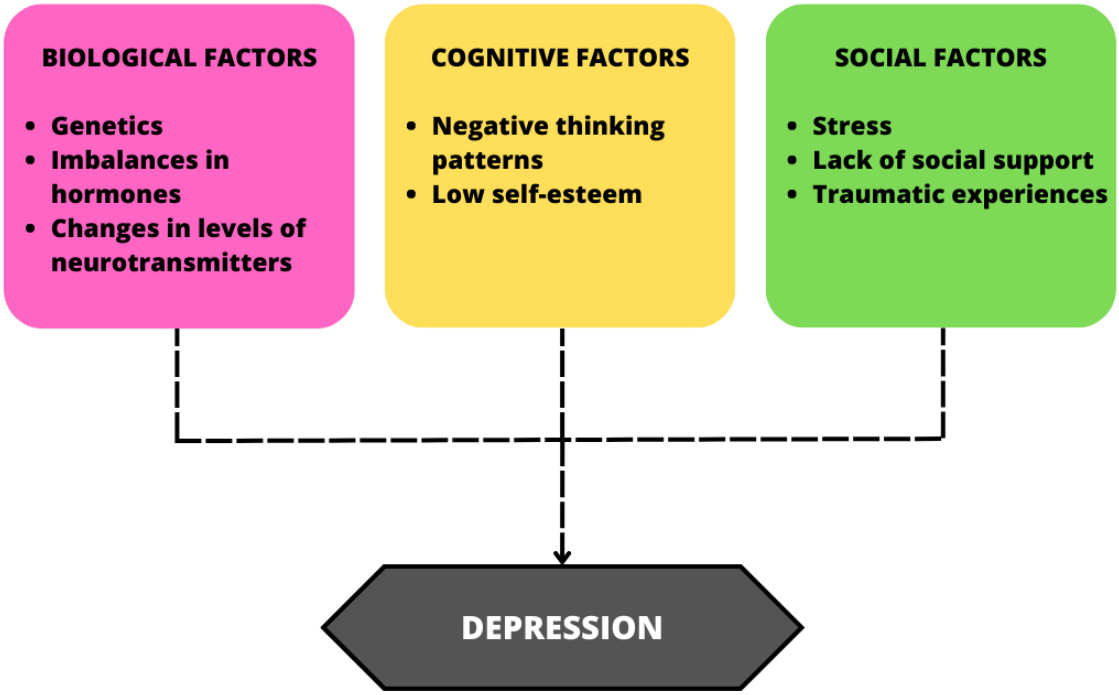

Figure 1.1 *Depression risk factors: biological, cognitive, and social domains.*

Understanding these risk factors and addressing them through various assessment and treatment approaches can help reduce the risk of depression and improve overall mental health.

As mentioned above, diagnosis of depressive disorders occurs when a subject satisfies a certain number of characteristics. However, suffering from depressive symptoms can occur without meeting the required diagnostic criteria. Such cases are commonly referred to as subclinical depression, or subthreshold depression, although in clinical psychiatry these labels are also used to describe residual states of a condition following a partial remission (Ji, 2012). Subclinical depressive symptoms such as feelings of sadness, loss of interest, changes in appetite or sleep patterns, fatigue, and a general sense of low mood can be observed as a manifestation of the interplay among biological, cognitive, and social risk factors in individuals not (yet) meeting the criteria for a diagnosis of depression. Data collected over time from a study involving 9900 adults revealed that individuals experiencing depressive symptoms were 4.4 times more prone to experiencing their first major episode of depression within a one-year period compared to those without such symptoms (Horwath et al., 1994). Similarly, a more recent systematic review conducted by Cuijpers and Smit (2004) demonstrated that the incidence of MDD among subjects with subthreshold depression was larger than in subjects without subclinical depressive symptoms. These findings indicate that depressive symptoms falling below the level required for a clinical diagnosis of MDD may serve as risk factors

for the development of depressive disorders. Furthermore, individuals experiencing subthreshold depression exhibit similarities to those with MDD across various aspects, including the level of functional impairment, the utilization of healthcare services, the occurrence of suicidal ideation, and the way they respond to treatments (Noyes et al., 2022). Given the widespread occurrence of depressive symptoms, which often go unnoticed and untreated in clinical settings, identifying these symptoms and establishing effective treatments could have significant public health implications. Doing so may help prevent the negative consequences of associated social distress, increased utilization of services, and the onset of major depression (Horwath et al., 1994).

1.2 Emotion Regulation

Depression is characterized by difficulties in regulating emotions: prolonged negative emotions and a consistent decrease in positive emotions are key indicators of depressive symptoms (Joormann & Gotlib, 2010). Emotion regulation (ER) is the individual modulation of the emotional response, which includes affective, experiential, cognitive, behavioural, and physiological elements occurring in reaction to significant events. Specifically, ER is the ability to control or influence both negative and positive emotions (McRae & Gross, 2020).

According to the Extended Process Model of ER (Gross, 2015), the process of controlling and influencing emotion can occur in all four stages of emotion generation (Figure 1.2a), namely experiencing relevant situations, paying attention to important aspects of those situations, evaluating the situation considering active goals (i.e., appraisal), and emotional response, which creates a new situation and starts a new cycle (McRae & Gross, 2020). In the Extended Process Model of ER, such stages allow for five types of ER strategy (Figure 1.2b) (McRae & Gross, 2020):

- *Situation selection:* situation selection strategies include actions geared towards enhancing the likelihood of being in situations that are expected to elicit desired emotions, or decreasing the probability of encountering situations that may give rise to undesired emotional experiences. Escaping a situation is an example of such strategies (i.e., avoidance).
- *Situation modification:* these strategies entail altering the characteristics of a situation to affect its emotional impact. An example of ER situation modification strategies is taking action to influence a situation once engaged.
- *Attentional deployment:* it involves the act of modulating emotional responses by redirecting attention within a specific situation. Consequently, attentional deployment can be seen as an internal counterpart to situation selection, as it entails the utilization of attention to determine which potential "internal situations" are activated for an individual at any given moment. Directing attention, whether internally or externally, away from the emotional context

towards non-emotional elements of the situation or entirely different non-emotional situations belongs to this category.

- *Cognitive change:* this group of ER strategies entails modifying one or more of the meanings associated with the situation (i.e., appraisals) in a manner that transforms its emotional significance by altering one's thoughts regarding either the situation itself or their ability to handle its challenges. A specific type of cognitive change that has garnered significant interest is known as *reappraisal*. Reappraisal involves altering the interpretation or understanding of a situation in a manner that leads to a shift in an individual's emotional reaction.
- *Response modulation:* it pertains to the direct influence on physiological, experiential, or behavioural responses. One extensively studied form of response modulation is expressive suppression, which involves deliberate efforts to diminish ongoing displays of emotional expression.

The first four types of ER strategies are "antecedent-oriented" because they focus on emotional aspects before the emotional response, as opposed to response modulation strategies that are "response-focused" (Gross, 1998). According to McRae and Gross (2020), the utilization of various emotion regulation (ER) strategies by individuals is influenced by certain governing processes (Figure 1.2c): as outlined in the process model, the ER cycle commences with the recognition of a disparity between an individual's desired emotional state (goal state) and their current or anticipated state. This disparity is then *identified* as a chance for regulation, leading to the *selection* of a regulation strategy from available alternatives. The chosen strategy is subsequently *implemented* through specific tactics, while the entire cycle is *monitored* to assess its effectiveness in achieving the intended regulatory objective.

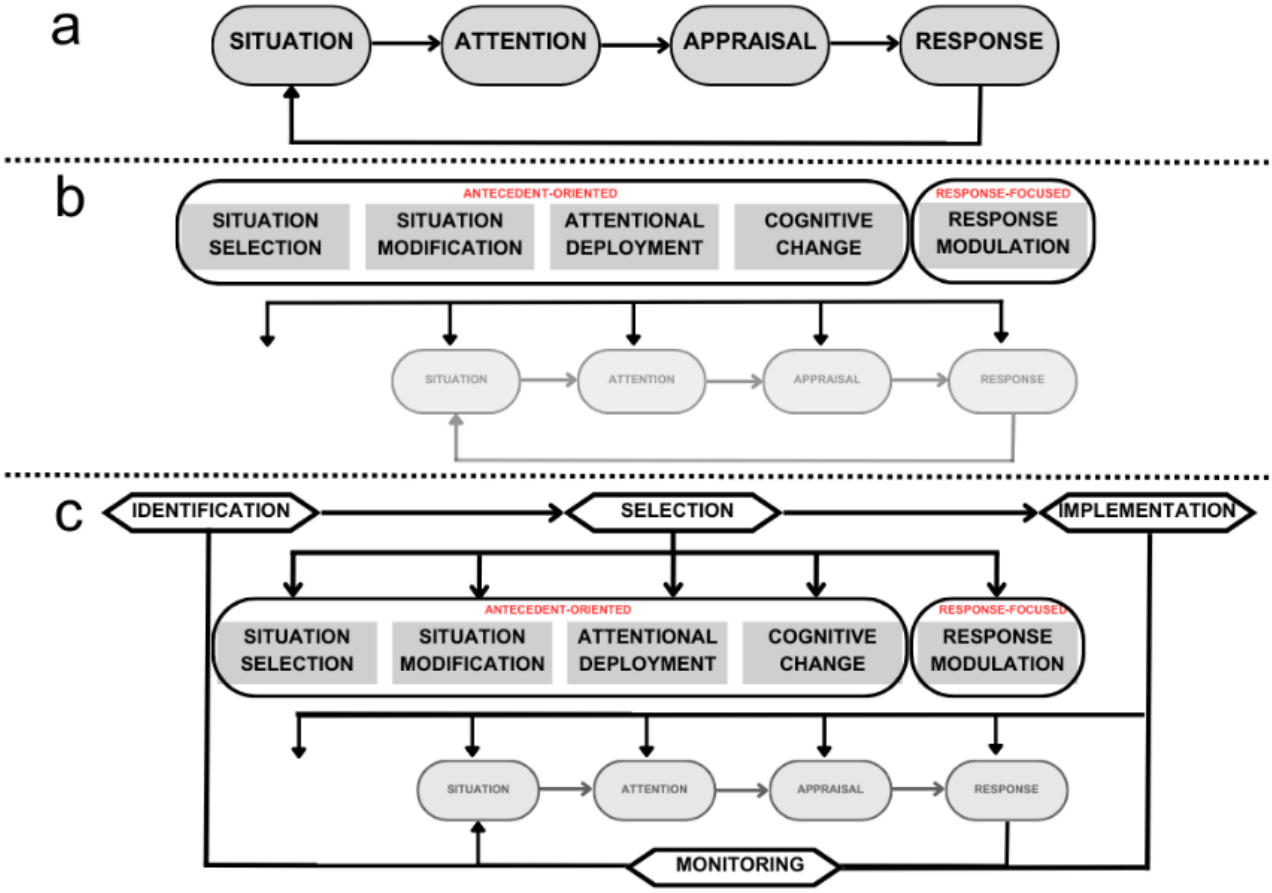

Figure 1.2 *The process model of emotion regulation. A sequential model of emotion regulation (a), the five categories of strategies for regulating emotions, categorized based on the stage at which they initially intervene (b), and the process model of emotion regulation, presenting four stages in which emotion regulation strategies are implemented (c). (Adapted from McRae & Gross, 2020).*

The following section will consider the role of cognitive factors in emotion regulation with a specific focus on the process of rumination.

1.2.1 Adaptive and Maladaptive Emotion Regulation: The Example of Rumination

It is believed that adequate ER is a requirement for psychological well-being, adaptive functioning in daily life (Nyklíček, 2011), and social functioning (English et al., 2012). ER strategies can be both adaptive and maladaptive. Reappraisal and problem solving are considered good examples of adaptive ER strategies in various contexts, as they involve employing functional approaches to alleviate distress. *Reappraisal* is a cognitive change strategy that entails reevaluating a situation in order to diminish distress, while *problem solving* is a situation modification strategy that reflects conscious efforts to alter a stressful situation or reduce its negative consequences, thereby diminishing the accompanying distress (Aldao et al., 2010). On the other hand, *suppression* and

avoidance have traditionally been regarded as dysfunctional strategies for various stressors (Aldao et al., 2010) and are known to increase the likelihood of experiencing distress and engaging in maladaptive behaviours. Multiple manifestations of suppression and avoidance have been associated with psychopathology. As mentioned before, Gross' model (2015) primarily focuses on the suppression of emotional expression (i.e., a response modulation strategy) and posits that while expressive suppression may initially diminish the outward display of emotions and potentially the subjective experience of emotions, its long-term effectiveness in reducing emotions and physiological arousal is limited. Avoidance refers to evading a range of psychological events, such as thoughts, emotions, sensations, memories, and urges (i.e., experiential avoidance; Hayes et al., 1999), or stressful scenarios (i.e., behavioural avoidance). Aldao et al. (2010) conducted a meta-analysis on the relationship between adaptive and maladaptive strategies with psychopathology (anxiety, depression, eating, and substance-related disorders). They found that maladaptive strategies were associated with more psychological distress, while adaptive strategies were not. Particularly, they found a large effect size for rumination associated with depression and anxiety (Aldao et al., 2010).

Rumination, as defined in the American Psychological Association (APA) Dictionary of Psychology (n.d.), is a pervasive form of thinking characterized by the presence of excessive and repetitive thoughts or themes that disrupt other mental activities. It is often associated with conditions such as obsessive-compulsive disorder, generalized anxiety disorder, and depression. According to McRae and Gross (2020) and their Extended Process Model of ER, rumination is considered a maladaptive ER strategy that prolongs and intensifies negative emotions, as opposed to the adaptive ER strategies mentioned above (i.e., reappraisal and problem solving), which are employed to diminish the negative aspects of emotion generation. Within this model, rumination represents an antecedent-oriented, attentional deployment strategy where individuals repeatedly redirect their attention towards the factors or consequences that trigger emotions. It involves a cyclical process of perseverating on negative experiences, leading to increased emotional activation, interference with adaptive ER strategies, and the maintenance of negative mood states (McRae & Gross, 2020).

1.2.2 The Role of Rumination in Depression Vulnerability

As previously noted, dysfunctional rumination is associated with depression. Many studies have tried to understand the nature of such an association, providing substantial evidence for the role of rumination in depression vulnerability. A recent meta-analysis conducted by Rickerby et al. (2022) found that rumination positively correlates with depressive symptoms. Furthermore, many research studies, including experimental, cross-sectional, and longitudinal investigations, have consistently demonstrated that rumination is linked to various aspects of depression. Specifically, rumination has

been shown to sustain and intensify depressed mood and serve as a predictor of increased levels of depressive symptoms (Papageorgiou & Wells, 2003).

A widely acknowledged model that attempts to explain the dynamics of the relationship between rumination and depression is the metacognitive model of rumination and depression (Figure 1.3; Papageorgiou & Wells, 2003). According to this model, *positive beliefs* about *rumination* motivate individuals to engage in persistent rumination, but they later perceive it as uncontrollable and harmful (*negative beliefs 1*). They also anticipate negative social consequences (*negative beliefs 2*), which contribute to *depression*. Decreased *metacognitive confidence and efficiency* further worsen negative beliefs and reinforce positive beliefs about rumination, interfering with the utilization of adaptive ER strategies and prolonging the experience of depressive mood. Therefore, this model suggests that self-perpetuating cycles involving metacognition and rumination contribute to the continuation of depression. The metacognitive model of rumination and depression is supported by empirical studies with both clinical and non-clinical samples (Cano-López et al., 2022).

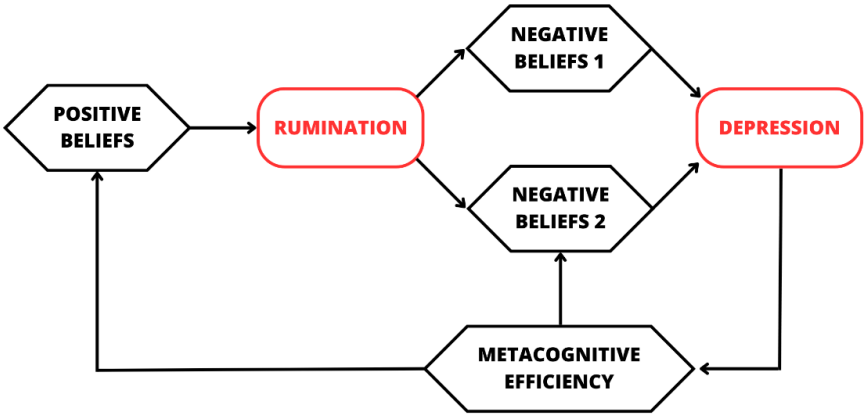

Figure 1.3 *The metacognitive model of rumination and depression. (Adapted from Papageorgiou, C., & Wells, A., 2003).*

CHAPTER 2

AUTONOMIC IMBALANCE IN EMOTION AND DEPRESSION

2.1 Autonomic Modulation of the Heart

The human nervous system is divided into two anatomically and functionally distinct branches: the central nervous system, which consists of the brain and the spinal cord, and the peripheral nervous system, made up of nerves travelling from the central nervous system to the rest of the body. The peripheral nervous system can be furtherly split into the somatic nervous system and the autonomic nervous system. The former carries sensory and motor information employed in voluntary movement, the latter is responsible for unconscious processes underlying the functional aspects of the organism, including heart rate, blood pressure, respiration, digestion, and sexual arousal (Waxenbaum, 2022).

Autonomic modulation is the result of the activity of two autonomic components, the Sympathetic Nervous System (SNS) and the Parasympathetic Nervous System (PNS). The modulatory activity of SNS and PNS was first believed to be reciprocal: the activation of one system would be associated with the inhibition of the other. According to this model, the autonomic activity would be described by a bipolar vector or continuum that goes from maximal SNS/minimal PNS activation to maximal PNS/minimal SNS activation (Figure 2.1a). However, Berntson et al. (1994) showed that a two-dimensional autonomic space better explains how autonomic modulation works (Figure 2.1b). The bivariate autonomic plane model includes the possibility of SNS and PNS coactivation and uncoupled activation.

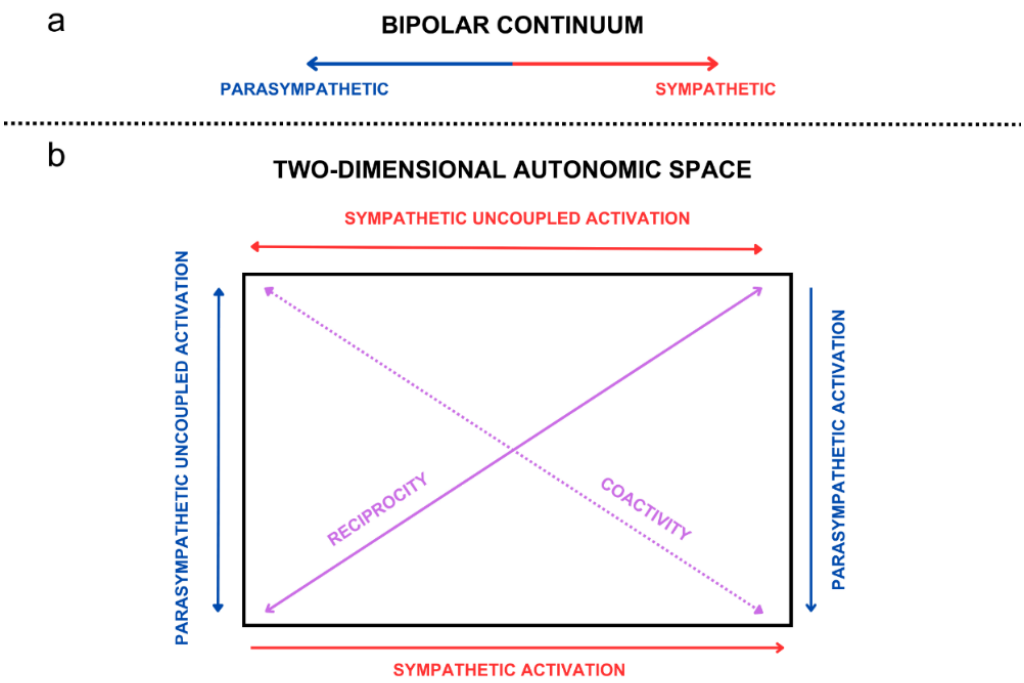

Figure 2.1 *Models of autonomic control. Note. This figure depicts two models of autonomic control: the bipolar continuum (a), and the two-dimensional autonomic space (b). (Adapted from Berntson et al., 1991).*

The autonomic modulation of heart rate is an example of the complexity of the SNS and PNS interactions. Such modulation supports the functional aspects of cardiovascular electromechanics in response to environmental stimulation, including stressful events and emotions. The autonomic nervous system exerts influence over the cardiac cycle, which refers to the sequential events involved in a complete heartbeat. The cardiac cycle consists of two primary phases, namely diastole and systole (Athanasiou et al., 2017). During diastole, the heart relaxes, allowing the atria to fill with blood and the ventricles to expand and prepare for blood reception. Systole follows, starting with the contraction of the atria to push any remaining blood into the ventricles. Once adequately filled, the ventricles contract, enabling blood ejection from the heart. After systole, the heart returns to diastole, and the cycle repeats. This continuous process ensures the constant circulation of blood throughout the body, supplying oxygen and nutrients to the tissues and removing waste products.

The heart is innervated by both SNS and PNS fibres, forming what is referred to as the cardiac plexus (Figure 2.2; Cacioppo et al., 2007). PNS afferents and efferents travel through the vagal nerve to and from the cardiac plexus; PNS heart innervation reduces heart rate and the contraction force of the cardiac muscle. Parasympathetic cholinergic fibers are more active during resting states, and they decrease heart rate by releasing acetylcholine (ACh) into their synapses with the sinoatrial (SA) and atrioventricular (AV) nodes, which contain pacemaker cells that originate the muscular contraction

in the heart (Gordan, 2015). On the other hand, SNS cardiac innervation consists of a group of fibers originating from the sympathetic ganglia located in the intermediolateral cell column of the thoracic spinal cord. that converge in the sympathetic chain; it is responsible for increasing heart rate and the contraction force of the myocardium. As opposed to PNS, SNS activity is higher in stressful situations, facilitating the typical 'fight or flight' response, or when the body requires high levels of energy (Gordan, 2015). When SNS is stimulated, its adrenergic fibres release norepinephrine (NE), which boosts the firing rate of SA and AV pacemaker cells, thus increasing heart rate.

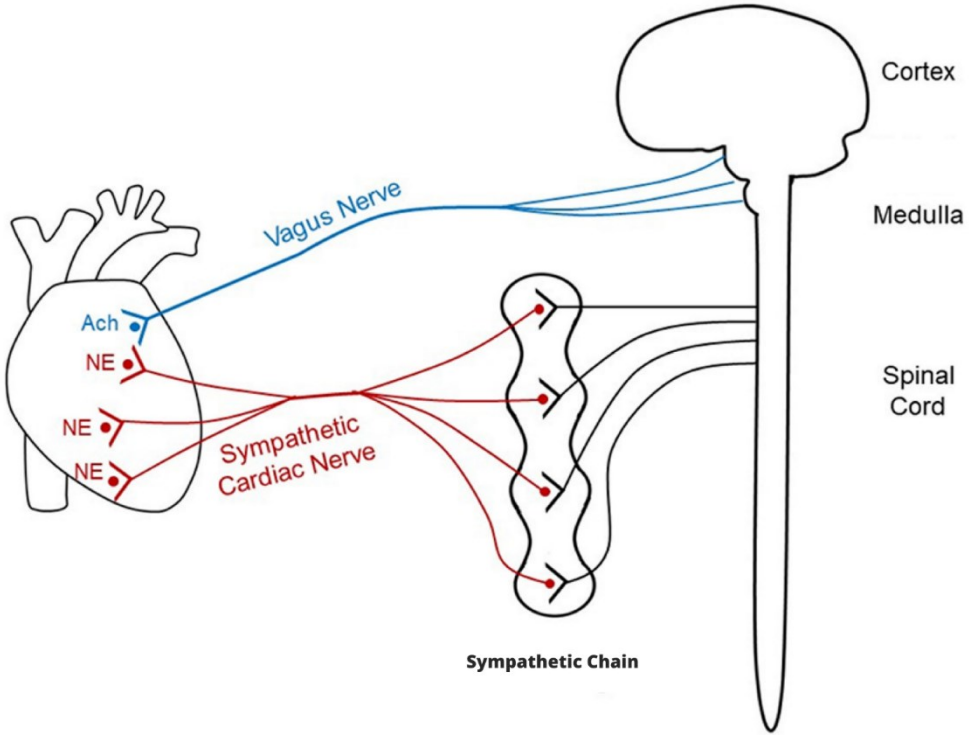

Figure 2.2 *Autonomic innervation of the heart. Ach = acetylcholine; NE = norepinephrine. (Adapted from Wan & Travin, 2020).*

2.1.1 Heart Rate Variability: Definition and Measurements

Heart Rate Variability (HRV) is defined as the range of fluctuations between heartbeats, influenced by the modulation of the autonomic nervous system on the heart. Higher variability is linked to lower heart rate values, whereas decreased HRV is observed when heart rates are faster (Task Force, 1996). In 1996, the Task Force of the European Society of Cardiology and the North American Society of Pacing and Electrophysiology published a paper with the intention of standardizing HRV nomenclature and measurements. In this paper, measurements of HRV are divided into two main categories: (a) time domain methods and (b) frequency domain methods (Table 2.1).

- *Time domain methods* can be obtained from information about interbeat intervals (IBIs), also called normal-to-normal intervals (NN), which are usually computed as the time distance between successive QRS complexes in an Electrocardiogram (ECG) signal. Simple time domain methods include the average NN interval, the average heart rate, and the difference between the longest and shortest NN intervals. Other time domain statistical methods can be computed over a series of instantaneous heart rates, especially if recorded over long periods, traditionally 24 hours. Among these measurements, the standard deviation of the NN intervals (SDNN), the root mean square of successive differences between NN intervals (rMSSD), and the number of interval differences of successive NN intervals greater than 50 ms (NN50) are the most common.
- *Frequency domain methods* rely on the Power Spectral Density (PSD) analysis, which offers the possibility to inspect the distribution of variance (i.e., power) as a function of frequency through mathematical algorithms such as the Fast Fourier Transform (FFT). HRV has four main frequency components or bands (Figure 2.3): (a) ultralow frequency (ULF, ≤ 0.003 Hz), (b) very low frequency (VLF, 0.0033-0.04 Hz), (c) low frequency (LF, 0.04-0.15 Hz), and (d) high frequency (HF, 0.15-0.40 Hz) (Shaffer & Ginsberg, 2017). There is still uncertainty on the biological nature of the ULF frequency band; however, it may involve very slow-acting processes such as circadian rhythms and metabolism. The VLF band seems to depend mainly on the heart's intrinsic nervous system and SNS modulation, although the debate on its physiological correlates is still open. More consistent evidence can be found on the physiological mechanisms behind the LF and HF bands: the former is related to the baroceptor activity during rest and might be influenced by both PNS and SNS modulation; the latter indexes vagal modulation (i.e., PNS), and it is also called the respiratory band because it mirrors HR alterations related to the respiratory cycle. Spectral components can be estimated with such methods on either short-term or long-term recordings. Short-term recordings (two to five minutes) allow for the computation of VLF, LF, and HF components, while ULF components can be extrapolated from long-term recordings only. The spectral components are usually expressed in absolute values of power (ms^2).

	Variable	Unit	Description
Time-domain	SDNN	ms	The standard deviation of the NN intervals
	rMSSD	ms	The root mean square of successive differences between NN intervals
	NN50		The number of interval differences of successive NN intervals greater than 50 ms
Frequency-domain	VLF	ms^2	Power in very low frequency range (0.0033-0.04 Hz)
	LF	ms^2	Power in low frequency range (0.04-0.15 Hz)
	HF	ms^2	Power in high frequency range (0.15-0.40 Hz)

Table 2.1 *Summary table of most common HRV measures used with (ultra) short-term recordings. (Adapted from Task Force, 1996).*

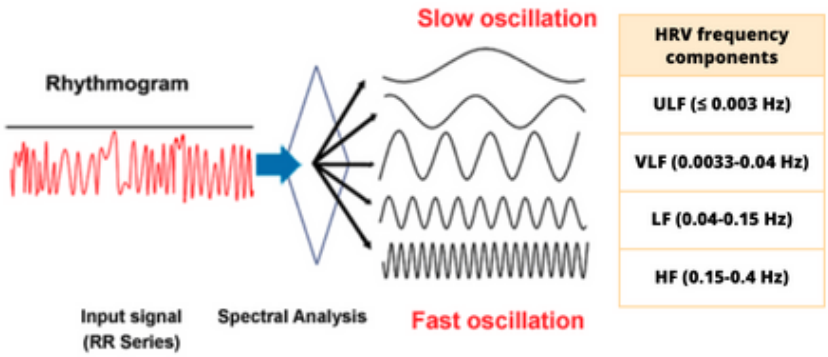

Figure 2.3 *Heart Rate Variability: frequency components. HRV = heart rate variability; ULF = ultra-low frequency; VLF = very low frequency; LF = low frequency; HF = high frequency.*

2.2 The Relevance of Heart Rate Variability in Healthy Adaptation, Cognition and Emotion

The clinical relevance of HRV was first acknowledged in 1963 by Hon and Lee, whose work proved how alterations in IBIs could precede fetal distress even before these changes could be visible in heart rate. In 2014, Shaffer et al. emphasized that "a healthy heart is not a metronome," highlighting the notion that a healthy heart does not exhibit a perfectly regular rhythm. Indeed, HRV reflects the ability of interdependent systems to adapt to different situations and respond functionally (Shaffer et al., 2014). Thus, healthy biological systems display a certain level of complexity, and deviations in this complexity can indicate disease.

Besides its role in general adaptability, HRV is also associated with cognitive processes. In a recent meta-analysis, Forte et al. (2019) investigated the relationship between cognitive functioning and autonomic modulation indexed by HRV. Although the evidence is relatively small when facing specific domains, they found that ANS modulation influences several cognitive functions, including global cognition, attention, and executive functions. Overall, the study concluded that higher high-frequency HRV was associated with better cognitive performance, while lower high-frequency HRV was linked to cognitive impairment (Forte et al., 2019). The relationship between HRV and cognition extends to affective functions as well. Emerging research suggests a connection between emotion regulation and HRV through shared brain regions (Mather & Thayer, 2018). Notably, a meta-analysis demonstrated a significant relationship between HRV and regional cerebral blood flow in the ventromedial prefrontal cortex, including the anterior cingulate regions, as well as the amygdala (Thayer et al., 2012). In both younger and older adults observed during rest, higher HRV corresponded to increased functional connectivity between the medial prefrontal cortex (MPFC) and amygdala (Figure 2.4; Sakaki et al., 2016), indicating a pattern linked to emotion regulation. This association suggests that ANS influences emotion regulation via overlapping brain areas.

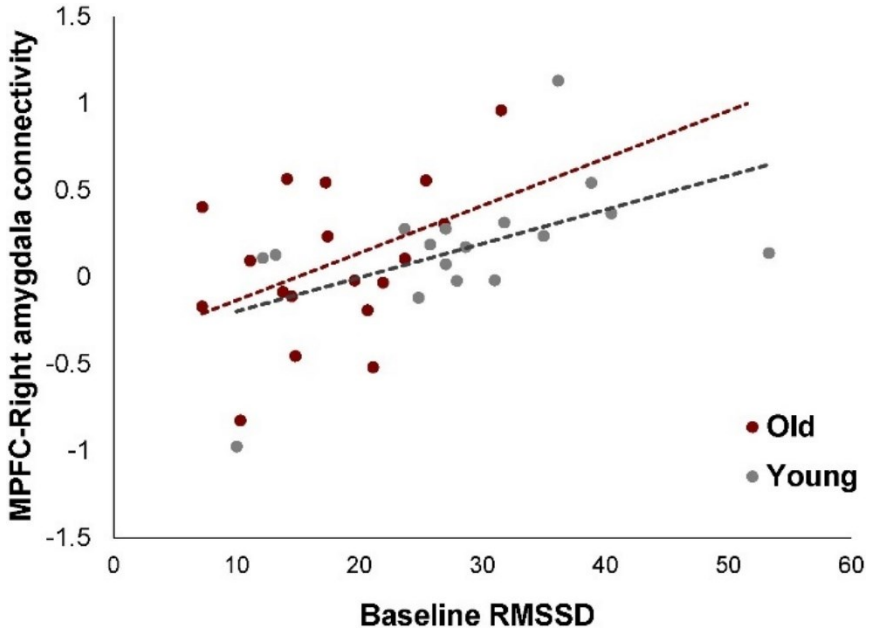

Figure 2.4 *Higher resting state HRV (rMSSD) is associated with increased functional connectivity between the medial prefrontal cortex (MPFC) and the right amygdala in both younger and older adults. (Adapted from Sakaki et al., 2016).*

Furthermore, environmental stimulation affects HRV: Kim et al.'s literature review (2018) demonstrated that stressful and harmful stimuli caused changes in HRV variables specifically indicating substantial evidence linking stress and low parasympathetic activity (Kim et al., 2018).

Considering the association between HRV and adaptability, cognitive and affective processes, and its response to environmental stimulation, particularly stress, HRV presents an avenue for exploring its clinical significance in evaluating the mental well-being and overall functioning of individuals.

2.3 Heart Rate Variability and Depressive Symptoms

The possibility to measure cardiac autonomic regulation with indices of HRV opened new perspectives of research in medicine and psychophysiology: a wide range of studies have investigated its potential as a risk assessment tool for many clinical conditions, including cardiovascular disease, psychiatric disorders and psychological distress (Gorman & Sloan, 2000; Xhyheri et al., 2012; Billman, 2011).

Because of the high occurrence of cardiovascular disease in patients with MDD (Stapelberg et al., 2012), the relationship between reduced HRV and depression has been one of the most explored among the psychological conditions associated with autonomic dysfunction: a simple "depression and heart rate variability" search in PsycINFO returns 3,917 hits. Over the past decade, the scientific community has shown great interest in considering heart rate variability (HRV) as a potential

biomarker for depressive symptoms: Kemp et al. (2010) concluded that patients with depression showed lower levels of HRV, even when they did not suffer from cardiovascular disease. Bassett (2015) conducted a literature review of HRV on unipolar and bipolar disorders, finding substantial evidence of autonomic dysregulation indicated by lower HRV levels in depression. Furthermore, changes in HRV seem to correlate with depression severity (Hartmann et al., 2019).

Recent studies suggest that reduced HRV may be a risk factor for depression, rather than one of the consequences (Koch et al., 2019; Huang et al. 2018). These findings indicate that HRV could be implemented in the diagnosis, prognosis, and treatment of depression (for a meta-analysis see Choi & Jeon, 2020). Over the past few years, an HRV-based treatment called Heart Rate Variability Biofeedback (HRV-BF) has been tested for several psychological disorders, including depression. HRV-BF consists of a procedure through which subjects are provided with online feedback on their heart rate data during slow breathing techniques; its purpose is to actively reach maximized Respiratory Sinus Arrhythmia (RSA), which is a measure of HRV (Lehrer & Gevirtz, 2014). In 2021, Melnikov reviewed six studies that tested HRV-BF on patients with major depression or other depressive disorders; based on the evidence, he concluded that HRV-BF is probably efficacious.

2.4 Heart Rate Variability and Rumination

According to the Perseverative Cognition Hypothesis (PCH) summarized in Figure 2.5, even when experienced at nonclinical levels, both conscious and unconscious perseverative cognitive processing of stressors triggers a "fight-or-flight" response, followed by a series of physiological changes that begin in the brain and manifest as peripheral stress responses like increased heart rate, blood pressure, and the release of stress hormones such as cortisol (Brosschot et al., 2010; Brosschot et al., 2006). Such cognitive processes include worry and rumination. The term "perseverative" emphasizes the focus on the prolonged exposure to the cognitive representation of the stressor, extending well beyond its actual occurrence. Consequently, persistent emotional or physiological activation can ultimately impact an individual's health, serving as a crucial mediator in the relationship between stress and disease.

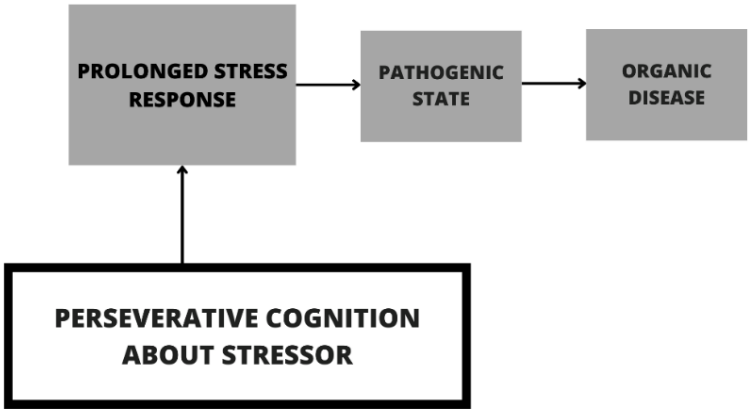

Figure 2.5 *The perseverative cognition hypothesis. (Adapted from Brosschot et al., 2006).*

Ottaviani et al. (2016) conducted a systematic review and meta-analysis to investigate the physiological correlates of perseverative cognition in healthy subjects, concluding that these processes are associated with lower HRV, along with other physiological variables. Another study concluded that state, mood-dependent rumination measured with RRS is more related to state HRV (rMSSD) than trait reflection (i.e., reflection as a relatively stable personality feature rather than a context-dependent characteristic) (Figure 2.6; Kocsel et al., 2019). Recent evidence suggests that this association is moderated by cognitive reappraisal, such that rumination is associated with lower HRV (RSA) only when subjects display low levels of cognitive reappraisal. These findings suggest that perseverative cognition such as rumination is associated with dysfunctional autonomic modulation.

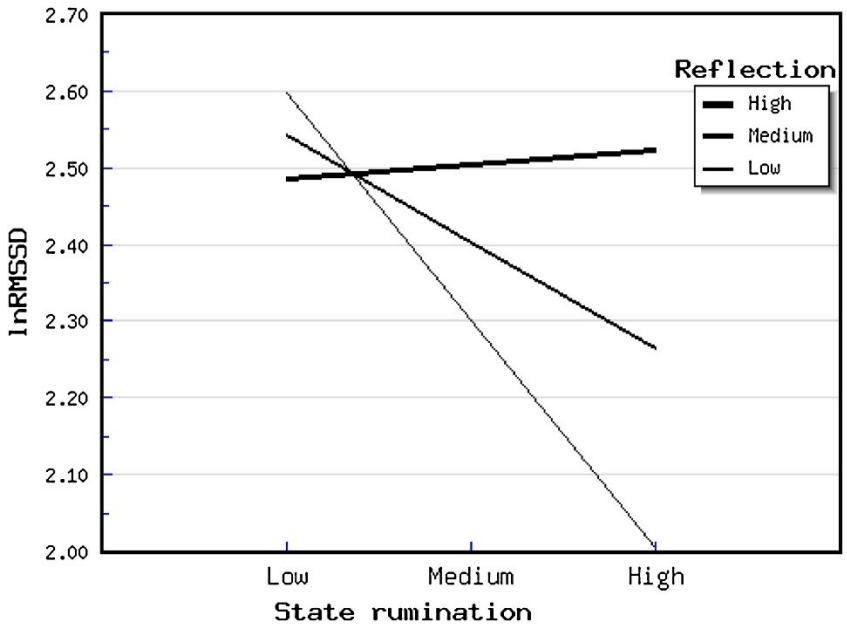

Figure 2.6 *Moderator role of personality trait reflection in the relationship between state ruminative thoughts and resting HRV (lnrMSSD). (Adapted from Kocsel et al., 2019).*

2.5 Heart Rate Variability, Rumination, and Depressive Symptoms.

Up to this point, theoretical models and empirical evidence have been presented to demonstrate the association between maladaptive strategies for regulating emotions, particularly rumination, and depression. Additionally, the connection between dysfunctional autonomic heart rate modulation, indicated by low HRV, and both depression and rumination, has been established. Furthermore, a recent study conducted by Moretta and Messerotti Benvenuti (2022) revealed how elevated levels of ruminative thinking and decreased HRV could potentially serve as early markers of susceptibility to depression.

Given these dynamics, there is a potential for HRV to act as a moderator in the relationship between rumination and depressive symptoms. In this scenario, it is conceivable that lower levels of HRV could enhance this association. Recently, this hypothesis has interested the scientific community. Carnevali et al. (2018) conducted a longitudinal study that showed how autonomic dysfunction, specifically a decreased vagal tone, could potentially play a role in the development of depressive symptoms in a non-clinical context. More recently, Dell'Acqua et al. (2021) investigated the moderating role of HRV in the relationship between depressive symptoms and brooding rumination through an empirical study that involved a non-clinical sample with different levels of depressed mood. Based on their results (Figure 2.7), they suggested an integrated model where vagally mediated HRV strengthens the positive association between depressive symptoms and brooding rumination.

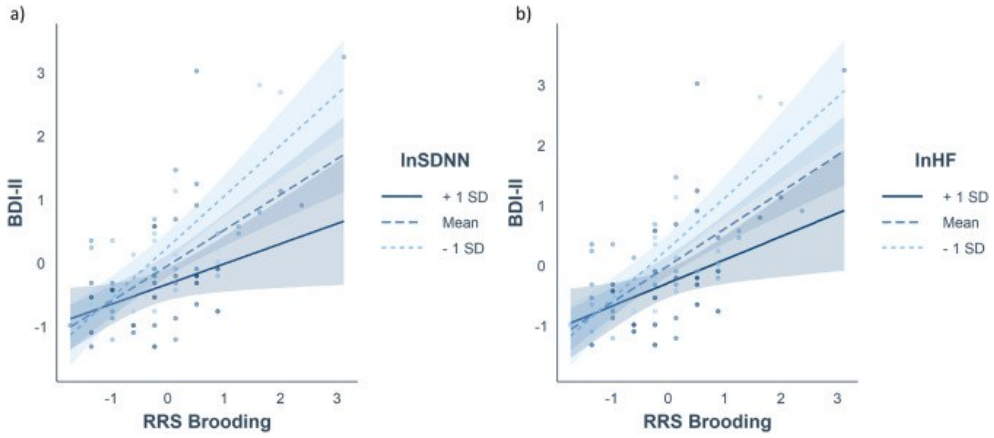

Figure 2.7 *The moderating role of HRV (lnSDNN) in the relationship between depressive symptoms (BDI-II) and brooding rumination (RRS). (Adapted from Dell'Acqua et al., 2021).*

While further research is necessary to gain a deeper understanding of how autonomic heart rate modulation, emotion regulation, and depression interact with each other, the most recent discoveries provide a potential avenue for exploring new prospects for depression prevention and treatment.

PART II

CHAPTER 3

THE RESEARCH

3.1 Introduction and Hypotheses

In the previous chapters, depression has been described in terms of symptomatology, risk factors, and its association with maladaptive emotion regulation strategies, specifically with rumination (Cano-López et al., 2022; Papageorgiou & Wells, 2003). Furthermore, substantial evidence was presented for the role of dysfunctional autonomic modulation as indexed by low HRV in the expression of both depressive symptoms (Hartmann et al., 2019; Basset, 2015; Kemp et al., 2010) and emotion dysregulation (Kocsel et al., 2019; Ottaviani et al., 2016; Brosschot et al., 2010; Brosschot et al., 2006). These associations provide the possibility to better understand the dynamics in the interplay of depression, rumination, and autonomic modulation. As mentioned above, such connections suggest that HRV could be a moderator in the association between rumination and depression (Moretta & Messerotti Benvenuti, 2022; Dell'Acqua et al, 2021). Considering that promotion, prevention, and early intervention strategies have the potential to significantly influence health and well-being, acquiring a deeper understanding of these processes could offer novel perspectives in the treatment of depression for individuals who are at a higher risk (Colizzi et al., 2020). This is particularly true for youth mental health: the transition from childhood to young adulthood is when most mental disorders emerge, affecting a considerable proportion of individuals before the age of 25 (Colizzi et al., 2020).

This study aimed to provide additional evidence regarding the role of rumination and vagally mediated heart rate variability (HRV) in determining depressive symptoms in a cohort of university students experiencing emotional distress and seeking psychological support. In addition, this study explored the potential moderating role of HRV in the association between rumination and depressive symptoms.

The choice to involve university students in the present study was based on their increased risk of depression for several reasons: (a) the demands of higher education, such as exams, assignments, and the pressure to perform well academically, can significantly contribute to stress and feelings of inadequacy, potentially leading to depression (Asif et al., 2020); (b) university life can sometimes lead to social isolation, particularly for students who are away from their families and old friends. Feelings of loneliness and social disconnection can contribute to depressive symptoms

(Huang, 2017); (c) irregular sleep patterns, poor nutrition, and inadequate self-care are common challenges for university students, which can negatively impact mental health and increase the risk of depression (Lund et al., 2010).

Building upon previous research, the hypotheses were as follows: (a) higher levels of rumination would be associated with greater depressive symptoms; (b) reduced levels of HRV would be associated with greater depressive symptoms; and (c) HRV would represent a moderator underlying the relation between rumination and depressive symptoms.

3.2 Methods

3.2.1 Participants

Forty-two participants took part in the present study (12 males, 29 females, 1 unspecified; mean age (M) = 23.3, standard deviation (SD) = 2.6). These individuals were university students experiencing emotional distress and seeking psychological assistance at the Psychology Clinic of the University of Padua (Servizio di Assistenza Psicologica per studenti universitari dell'Ateneo di Padova, SAP). They were presented with the opportunity to participate in the study during the acceptance and preliminary assessment phase at SAP. Interested participants were directed to the involved clinicians, where they were provided with comprehensive information about the study. After a thorough explanation of the study's procedure, participants volunteered to sign the informed consent form. The consent form included authorization to access data collected by the SAP clinicians during the preliminary assessment phase, including information about gender, age, medical history, drug use, sleep, smoking, and drinking habits. Exclusion criteria included a current or past history of cardiovascular, psychiatric, and neurological diseases, as well as the consumption of psychotropic substances or an excessive quantity of alcohol and tobacco.

3.2.2 Self-Report Questionnaires and Scoring Procedure

Depressive symptoms were evaluated using the Beck Depression Inventory-II (BDI-II; Beck et al., 1996; Italian version by Ghisi et al., 2006). The BDI-II is a reliable and valid self-report questionnaire utilized to assess the severity of current depressive symptoms over the past two weeks. It consists of 21 items, each rated on a four-point Likert scale ranging from 0 to 3, with final scores ranging from 0 to 63, corresponding to the total sum of the single items. Higher scores indicate more pronounced depressive symptoms. According to the Italian validation of the BDI-II (Ghisi et al., 2006), a score of 11 or below indicates the absence of depression, scores between 12 and 21 represent mild-to-moderate depression, and scores equal to or above 22 correspond to severe depression (99th percentile).

Rumination was measured using a part of the Response Style Questionnaire (RRQ; Nolen-Hoeksema & Morrow, 1991), the Ruminative Response Scale, (RRS; Treynor et al., 2003; Italian version by Palmieri et al., 2007). Although the RRS has undergone some modifications over time, the various versions remain highly comparable (Roelofs et al., 2006). The original RRS comprises 22 items, including five brooding items (e.g., "think about a recent situation, wishing it had gone better"), five reflection items (e.g., "analyze recent events to try to understand why you are depressed"), and 12 depression items (e.g., “think about how passive and unmotivated you feel”). Participants rate their agreement on a Likert scale ranging from 1 (never) to 4 (always). The RRS has demonstrated excellent internal consistency and validity (Treynor et al., 2003). In 2007, Palmieri et al. conducted a validation study for the RRS with an Italian sample. Based on their results, the original RRS three-factor structure was confirmed, although there was a difference in the items that each component comprised. Specifically, six more items were included in the brooding factor, for a total of 11 items, while only six items saturated the depression component; the reflection items corresponded to the original structure. In this study, the analysis focused on RRS total scores, which were calculated by the sum of individual answers to all 22 items. This choice was based on the fact that the RRS total score provides a comprehensive assessment of an individual's overall levels of rumination.

To prevent any potential systematic errors resulting from manual calculations, the scoring procedure was entirely performed using RStudio (RStudio Team, 2020).

3.2.3 Heart Rate Recording

Heart rate data was obtained using a remote smartphone-based method called Camera Heart Rate Variability that relies on Photoplethysmography (PPG), which is a non-invasive technique used to measure changes in blood volume in tissues (Pai et al., 2021). The method involves a light source, typically a Light Emitting Diode (LED), that sends a luminous signal through the skin and into blood vessels. As blood absorbs light, the amount of light transmitted or reflected back is detected by a photodetector. The resulting signal, known as a photoplethysmogram (PPG), represents the variations in blood volume, which are associated with the cardiac cycle (Figure 3.1). PPG is a reliable alternative to the electrocardiogram (ECG) and provides highly correlated heart rate variability (HRV) indexes when measured at rest (Menghini et al., 2019). The accuracy of PPG recordings using Camera Heart Rate Variability has been found to be satisfactory (Pai et al., 2021).

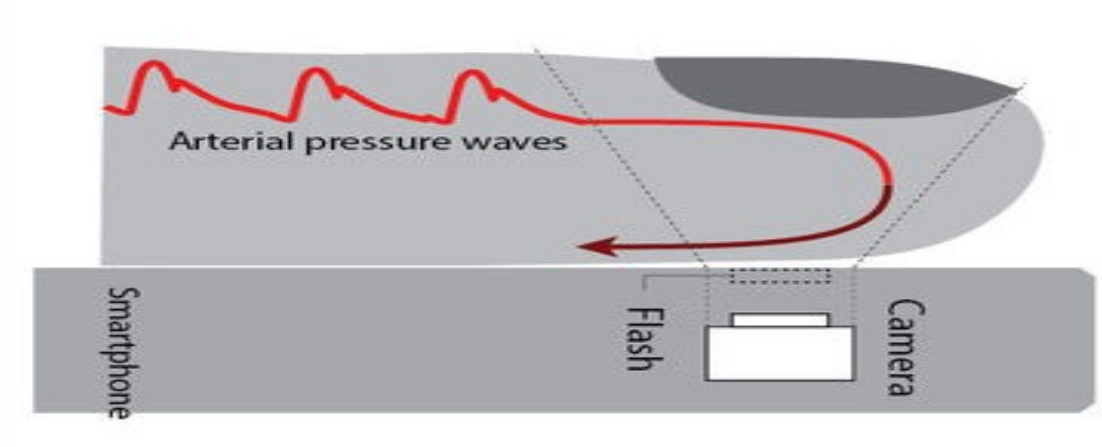

Figure 3.1 *Smartphone-based Photoplethysmography (Adapted from Vandenberk et al., 2017).*

3.2.4 HRV Data Reduction

The Camera Heart Rate Variability app provided an index of accuracy based on the recordings' reliability (poor, good, or optimal recordings). Only optimal recordings were considered for this study. The analysis of heart rate variability (HRV) involved offline processing of RR intervals using Kubios HRV Analysis Software 3.3.1 (Tarvainen et al., 2014). Stable periods of 30 seconds with the most accurate 1-minute recording were selected among the recordings obtained from each participant (Munoz et al., 2015). To correct artifacts, a piecewise cubic spline interpolation method was applied. The segments were also manually checked for artifacts (e.g., extreme values).

The root mean square of successive differences between NN intervals (rMSSD) was calculated in milliseconds to reflect the short-term variability of heart rate. rMSSD is highly sensitive to fluctuations in the high-frequency component of HRV and serves as an index of vagal control over the heart (Laborde et al., 2017; Task Force, 1996). Among the time-domain measures, rMSSD was considered the most appropriate HRV measure for short-term recordings (Laborde et al., 2017; Task Force, 1996) and the most valid measure for HRV in (ultra-)short recordings (Munoz et al., 2015). Furthermore, rMSSD is less affected by respiratory and movement artifacts compared to other time-domain and frequency-domain indices (Penttilä et al., 2001).

3.2.5 Statistical Analyses

Variables such as gender, age, and sleep, smoking, and drinking habits have been identified as potential factors affecting resting heart rate variability (HRV), as stated by Laborde et al. (2017). To assess the impact of these variables on resting HRV, preliminary analyses were conducted. Pearson's correlations were calculated to examine the relationships between the HRV parameter and age, sleep duration (average hours per night), smoking (number of cigarettes per day), and alcohol consumption (units per week). Furthermore, Cronbach's alpha was computed to determine the internal consistency

of the self-report questionnaires (BDI-II and RRS). All questionnaires' scores underwent a process of centering and scaling, wherein the mean of each variable was subtracted from each value. The resulting value was then divided by the standard deviation of its distribution.

Pearson's correlations were calculated to examine the relationships among the study variables. A linear regression analysis was employed to investigate the relationships between rumination (assessed using the RRS), depressive symptoms (measured by the BDI-II), and vagally mediated heart rate variability (represented by rMSSD). Additionally, the study aimed to examine the moderating effect of heart rate variability on the association between rumination and depressive symptoms. To this end, the mean-centered BDI-II score has been selected as dependent variable, while the potential predictors included the HRV measure (rMSSD) and the mean-centered RRS score. A two-way interaction term (RRS x rMSSD) has also been considered. A significance level of $p < .05$ was used as the threshold for determining statistical significance.

The statistical analyses were entirely performed with Jamovi (The Jamovi project, 2023).

3.3 Procedure

Participants completed an online assessment using Google Forms, which included the Beck Depression Inventory-II (BDI-II; Beck et al., 1996) and the Ruminative Response Scale (RRS; Nolen-Hoeksema & Morrow, 1991) questionnaires. PPG data collection sessions were scheduled either early in the morning or in the afternoon, ensuring they were conducted away from meals. Participants were given instructions to avoid smoking and coffee and alcohol consumption before the recording session. Prior to PPG data collection, participants were provided with detailed instructions. They were asked to sit upright in a quiet room and place the smartphone's camera on their index finger in a manner that applied no unintended pressure to the camera. Participants were directed to maintain normal breathing patterns and avoid any form of communication, whether verbal or non-verbal, during the data collection process. For data recording, the smartphone's camera served as a light receiver, and the LED flashlight served as the light source. A video stream at a frame rate of 30 Hz was acquired. While the Task Force guidelines (1996) suggest an optimal sampling rate of around 100 Hz, lower sampling rates are deemed acceptable when interpolation algorithms are applied to enhance the accuracy of R-wave detection (Task Force, 1996). To address this, the signal quality was enhanced by employing cubic spline interpolation to up-sample the signal from 30 to 180 Hz. RR intervals, representing the time between consecutive heartbeats, were collected for a duration of 1 minute. Peak-to-peak intervals were identified through a peak detection algorithm based on slope inversion, and automatic artifact correction procedures were implemented. This entire procedure was conducted remotely (via Zoom call) and took approximately thirty minutes to complete.

3.4 Results

3.4.1 Descriptive Statistics

A total of eleven participants were excluded from the study. Five participants were excluded due to missing physiological data, one participant was excluded because of a reported history of epilepsy, and an additional five participants were excluded due to a lack of optimal physiological recordings. Analyses were performed on a final sample (N = 31) consisting of 10 males (32%) and 21 females (68%), with an average age of 23 (SD = *2.3*). On average, participants consumed one unit of alcohol per week (standard deviation = 0.7) and smoked 0.3 cigarettes per day (standard deviation = 0.6). Out of the total participants, six individuals slept an average of less than six hours per day, thirteen participants slept between seven and nine hours daily, and two participants slept for more than nine hours each day. Gender, age, and sleep, smoking, and drinking habits did not show significant correlations with the HRV measure (Table 3.1; all p-values > .05).

The descriptive statistics of the psychological measures (BDI-II, RRS) and HRV are reported in Table 3.2. Internal consistency resulted high for both the 21 items of the BDI-II (Cronbach's alpha α = 0.85) and the 22 items of the RRS (Cronbach's alpha α = 0.89). Out of the total sample of participants, 11 individuals (35.5%) had a BDI-II score of 11 or lower, indicating the absence of depression. 11 participants (35.5%) had scores between 12 and 21, suggesting mild-to-moderate depression, while 9 participants (29%) had scores above 22, indicating severe depression. Normative values for RRS total scores and rMSSD are not available for reference. However, a study by Moretta and Messerotti Benvenuti (2022) reported mean values of RRS (mean RRS score = 36.3, standard deviation = 8.2) and rMSSD (mean rMSSD = 66.6, standard deviation = 27.5) in a control group with similar demographic characteristics to our present study. Compared to the sample in the study mentioned above, the present study's sample registered a higher mean RRS score (mean RRS score = 50, standard deviation = 10.2) and a lower mean rMSSD (mean rMSSD = 52.2, standard deviation = 24.5).

Variable	Gender	Age	Sleep duration	Drinking habits	Smoking habits
rMSSD	-.32	-.24	.11	-.09	.19

Table 3.1 *Pearson's correlations between the HRV measure and sociodemographic (gender and age) and life habits (sleep duration, drinking habits, and smoking habits). rMSSD = root mean square of successive differences between NN intervals. Note. All p – values > .05.*

Study Variable	Mean	Standard Deviation	Range (Min-Max)
BDI – II scores	15.6	7.9	2-35
RRS scores	50	10.2	29-71
rMSSD ms	52.2	24.5	25.7-151

Table 3.2 *Descriptive statistics of the study variables. Note. BDI – II = Beck Depression Inventory – II; RRS = Ruminative Response Scale; rMSSD = root mean square of successive differences between NN intervals; ms = milliseconds; Min = minimum value of the distribution; Max = maximum value of the distribution.*

3.4.2 The Association between Rumination and Depressive Symptoms and the Moderating Role of HRV

Results showed that the correlation between the BDI-II scores and the RRS scores was highly significant ($p < .001$) (Figure 3.2). There were no significant correlations between each subjective variable (BDI-II and RRS) and rMSSD ($p > .05$), however, the correlation between BDI-II and rMSSD was almost significant ($p = .05$). The correlations among the study variables are summarized in Table 3.3.

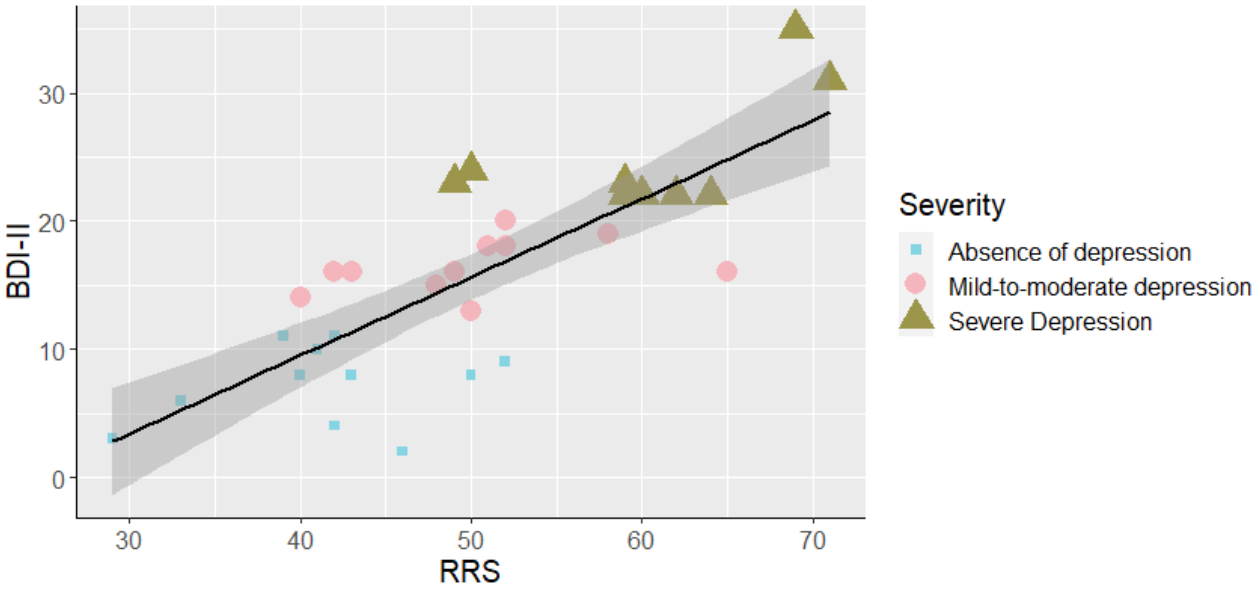

Figure 3.2 *Positive association between RRS and BDI-II scores. The graph also shows depression severity based on the categorization proposed in the Italian validation study of the BDI-II by Ghisi et al. (2006).*

	BDI – II	RRS	rMSSD
BDI – II	-		
RRS	***.79*** **	-	
rMSSD	*-.35*	*-.23*	-

Table 3.3 *Correlation (Pearson's) matrix for the study variables. **p < .01; BDI – II = Beck Depression Inventory – II; RRS = Ruminative Response Scale; rMSSD = root mean square of successive differences between NN intervals.*

The linear regression model with rMSSD, the mean-centered RRS scores, and their interaction as predictors of the mean-centered BDI-II scores is shown in Table 3.4. The independent effects of rumination and vagally mediated HRV (rMSSD) on BDI-II were both significant. Specifically, rumination was positively associated with depressive symptoms, while HRV (rMSSD) was negatively related to depressive symptoms (Table 3.4). Although the regression slopes indicate that rumination positively predicted depression levels, the association between RRS and BDI-II scores was stronger in individuals with lower rMSSD compared to those with higher rMSSD. Specifically, the link between high levels of rumination and depressive symptoms was most noticeable in individuals with low HRV, as demonstrated in Figure 3.3. Based on the results, vagally mediated HRV (rMSSD) is a significant moderator in the association between rumination (RRS scores) and depressive symptoms (BDI-II scores) (Table 3.4).

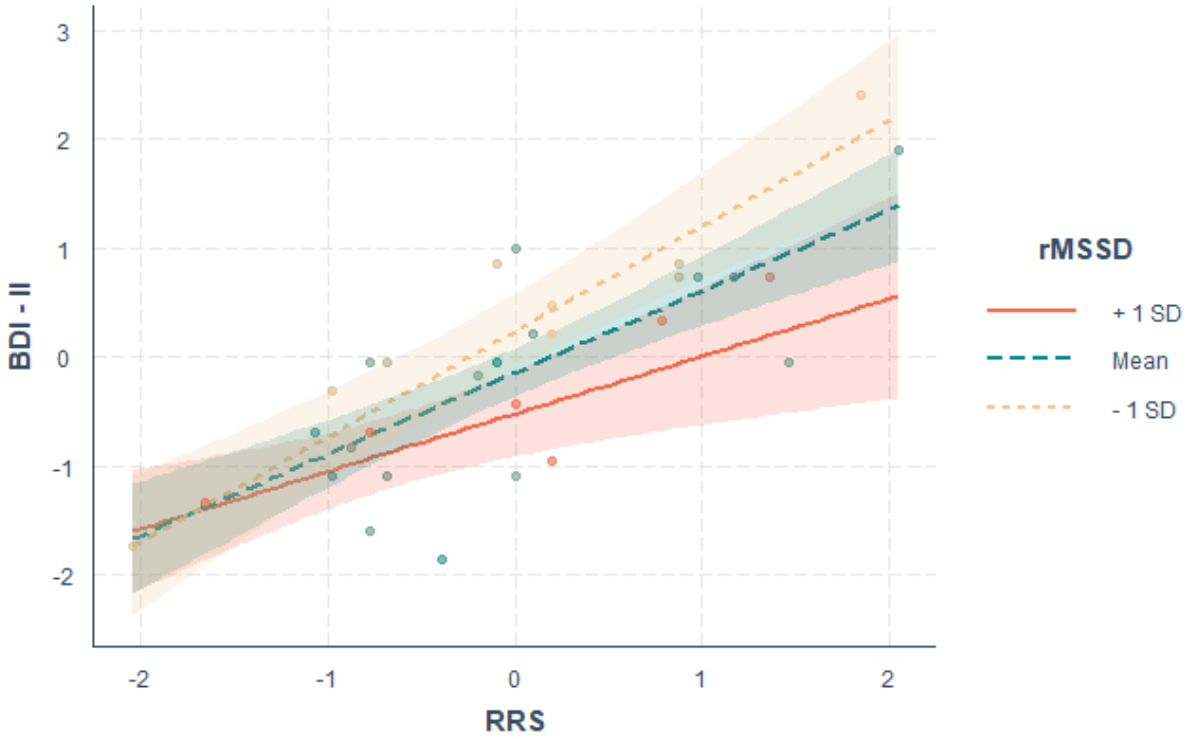

Figure 3.3 *Interaction effect of RRS and rMSSD on BDI-II. 95% confidence bands for mean (green line), +1 SD (red line), − 1 SD (yellow line) rMSSD are presented in different colors. BDI-II = Beck Depression Inventory – II; RRS = Ruminative Response Scale; rMSSD = square root of the mean squared differences of successive NN intervals.*

R^2	Predictor	Estimate (SE)	*t*	*p*
0.71				
	rMSSD	-0.02 (0.01)	-2.62	**.014**
	RRS	1.19 (0.23)	5.10	**<.001**
	RRS x rMSSD	-0.01 (0)	-2.09	**.046**

Table 3.4 *Linear regression model for variables predicting depressive symptoms (BDI – II); RRS = Ruminative Response Scale; MC = mean-centered; rMSSD = root mean square of successive differences between NN intervals; SE = Standard Error; t = Student's t.*

3.5 Discussion and Conclusion

The primary objective of this research was to investigate the relationship between rumination, vagally mediated heart rate variability (rMSSD), and depressive symptoms among university students seeking psychological assistance for emotional distress. To this end, levels of rumination and depression were assessed using self-report questionnaires, and resting state HRV was measured with photoplethysmography. Based upon prior research, it was hypothesized that both high levels of

rumination and low levels of vagally mediated HRV would be associated with higher levels of depressive symptoms and that low levels of HRV would potentiate the association between rumination and depression (Cano-López et al., 2022; Moretta & Messerotti Benvenuti, 2022; Dell'Acqua et al, 2021; Hartmann et al., 2019; Basset, 2015; Kemp et al., 2010; Papageorgiou & Wells, 2003).

The examination of independent effects revealed both rumination and vagally mediated HRV as significant contributors to depression. Specifically, rumination consistently emerged as a psychological predictor of depressive symptoms, while vagally mediated HRV served as a physiological marker associated with depression. These findings are in line with prior research that underscores the link between rumination and depression, providing further support for identifying rumination as a maladaptive strategy within the framework of the Extended Process Model of Emotion Regulation (Cano-López et al., 2022; McRae & Gross, 2020; Papageorgiou & Wells, 2003; Hartmann et al., 2019; Basset, 2015; Kemp et al., 2010). Additionally, the association between low levels of HRV (rMSSD) and depressive symptoms that emerged in this study is in line with past research investigating the role of autonomic dysregulation, specifically regarding PNS modulation, in the occurrence of psychological distress (Hartmann et al., 2019; Koch et al., 2019; Huang et al. 2018; Bassett, 2015; Kemp et al., 2010). Furthermore, low levels of vagally mediated HRV exhibited a significant moderating effect on the association between rumination and depression. Particularly, the strength of the relationship between rumination and depression displayed variations based on rMSSD levels: in individuals with low HRV, the influence of rumination appeared more pronounced, indicating a potential vulnerability to the development or exacerbation of depression within this subgroup.

These outcomes contribute to a better understanding of the interplay between cognitive processes and autonomic flexibility in the context of depressive symptoms. The interaction observed among rumination, vagally mediated HRV, and depression highlights the joint impact of psychological and autonomic influences on the manifestation of depressive symptoms, emphasizing the importance of considering such intricate interactions in elucidating the underlying mechanisms of rumination and its implications for mental well-being. Incorporating these findings into both research and clinical realms holds substantial promise.

From a clinical standpoint, understanding the dynamic interplay between rumination and vagally mediated HRV in relation to depression advances the development of targeted interventions. Individuals characterized by low vagal HRV and a propensity for rumination could potentially benefit from interventions that specifically address rumination and promote adaptive emotion regulation strategies. Moreover, the assessment of HRV may provide valuable insights into predicting susceptibility to depressive symptoms and designing treatment approaches accordingly.

This study is not without limitations. First, this was a cross-sectional study, constraining causal inferences and the examination of temporal relationships. Future longitudinal studies could shed further light on the dynamic nature of these associations. Furthermore, although participants received precise instructions from trained researchers during the physiological recording, conducting the study remotely could have introduced certain limitations in the recording of heart rate variability (HRV). It is recommended that future studies replicate the present findings in a controlled laboratory setting to address these potential distortions in HRV measurement. Finally, the sample size of the present study was relatively small, and the distribution of male and female participants was uneven, both factors that may affect the generalizability of the results.

In conclusion, this study emphasizes the moderating role of vagally mediated HRV in the link between rumination and depression. The outcomes underscore the joint significance of psychological and autonomic elements in comprehending depressive symptoms. The findings of the present study add to the growing body of literature surrounding the intricate interplay of cognitive processes, physiological markers, and mental health outcomes. Further exploration and clinical interventions targeting rumination and HRV hold the potential to enhance our understanding and management of depression.

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