

BACHELOR THESIS

IDENTIFYING TRAUMA SIGNATURES IN MEDICAL TIME SERIES DATA

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Abstract

Accurate assessment of psychological trauma and the objective quantification of therapeutic outcomes remain critical challenges in clinical practice. While standard diagnosis for Post-Traumatic Stress Disorder (PTSD) typically relies on subjective patient reports and standardized questionnaires, these methods can be susceptible to bias. This thesis explores Heart Rate Variability (HRV) as an objective physiological biomarker for quantifying the severity of trauma-related psychological distress. The aim is to identify changes in heart related time series data indicative of traumatic events. This research compared the HRV of patients diagnosed with Post-Traumatic Stress Disorder (PTSD) to a healthy control group. The data was acquired during a simulated Eye Movement Desensitization and Reprocessing (EMDR) therapy session. Results show a significant reduction in low frequency (LF) and high frequency (HF) power in patients with PTSD compared to healthy controls. The findings highlight the need for further investigation into the relationship between HRV and trauma. However strong evidence indicate that HRV, particularly LF and HF , can serve as a valuable tool for assessing ANS health and monitoring stress responses as well as distinct between patients with PTSD and healthy individuals.

Keywords: Heart Rate Variability; HRV; Post Traumatic Stress Disorder; PTSD; Autonomic nervous system; ANS; Electrocardiogram; ECG; Eye Movement Desensitization and Reprocessing; EMDR

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1 Introduction

This section will explain the significance and motivation of this research, outlining the specific areas of investigation and the objectives that will be pursued throughout the thesis.

Info. It is to note that the focus of the present work is not the analysis of a particular dataset, which is also why the data used in 6 is not fully described. The primary objective is to establish a data processing pipeline for ECG data. An initial analysis is conducted to test whether patient groups can be separated. This provides the basis for analyzing individual patient ECGs, for classification, and predicting changes during therapy.

1.1 Background & Motivation

Post Traumatic Stress Disorder (PTSD) is a mental health condition that can develop as a reaction to traumatic events such as war, assault or natural disasters [EC00]. PTSD is characterized by a range of symptoms including repeated reexperiencing of the event, hyperarousal as in being constantly on edge, being emotionally numb with a restricted range of feelings or also actively avoiding thoughts that could trigger memories of the trauma. Of those who experience trauma and develop symptoms, approximately half remit spontaneously without formal treatment. However for other groups with persistent PTSD, symptoms can continue for years, which can lead to impaired functioning in relationships, work and daily life. Those affected typically seek medical treatment.

This represents a significant challenge in modern healthcare, affecting numerous individuals worldwide through both physical injury and psychological distress [Koe+17; Kes+05; Sch+24; Cyr+21]. In this research, it is proposed that traumatic events trigger complex physiological responses across multiple body systems, producing distinctive patterns detectable through various biomedical markers. Despite advances in trauma care, the study of trauma’s physiological signatures holds great promise for therapeutics research and as an objective measure of symptom severity in patients with established Post-Traumatic Stress Disorder (PTSD).

Medical time series data, particularly electrocardiogram (ECG) recordings, offer a rich source of information about an individual’s physiological state. These continuous measurements can capture the dynamic nature of the body’s response to stress and injury through the autonomic nervous System (ANS), potentially revealing characteristic “signatures” associated with different types and severities of trauma. Specifically, Heart rate variability (HRV), has emerged as a promising biomarker that reflects the body’s adaptive capacity and overall physiological resilience, providing insights into stress response, recovery patterns, and the body’s general ability to maintain internal stability when under various pathological conditions, such as severe trauma and PTSD [IKK21; SS20].

Advances in signal processing techniques and algorithms have created excellent opportunities to extract meaningful information from these complex data streams. The increasing availability of wearable ECG monitors and other biosensors has also further expanded the potential applications of trauma detection beyond traditional clinical settings. However, challenges remain in processing noisy physiological signals, identifying relevant features, and developing interpretable models that

can inform clinical decision-making.

The motivation for this research lies in the potential to improve trauma care through objective detection of trauma signatures within ECG data. By identifying characteristic patterns that correlate with trauma burden, clinicians may be able to intervene more promptly and effectively during trauma therapy. Additionally, a deeper understanding of the PTSD-related physiological response pattern could contribute to the development and improvement of therapeutic strategies, such as CBT (Cognitive Behavioral Therapy), PE (Prolonged Exposure) or EMDR (Eye Movement Desensitization and Reprocessing).

1.2 Statement of Purpose

This thesis aims to investigate the potential of identifying trauma signatures in medical time series data, specifically focusing on electrocardiogram (ECG) recordings. One primary objective is to develop a comprehensive analytical framework that can effectively help to process, analyze, and visualize ECG data to detect patterns potentially associated with traumatic experiences or ongoing trauma responses.

Precisely, this research seeks to:

1. Explore the utility of heart rate variability (HRV) metrics and other derived features as biomarkers for general and PTSD-related physiological stress.
2. Implement and evaluate methodologies for preprocessing, feature extraction, and visualization of ECG data making it usable as effect measures for trauma-specific treatments.
3. Identify and characterize distinctive patterns in ECG signals that correlate with different severities of trauma burden.

Ultimately, the goal will be to advance the objective assessment of trauma by transforming raw ECG signals into clinically relevant features, thus providing quantifiable, physiological measurements to complement subjective psychological evaluations which may enhance diagnostic accuracy and treatment planning.

This goal poses specific questions that will be addressed throughout this research:

Q1 *How does HRV reflect the psychological state?*

Q2 *How can HRV be derived from ECG data?*

Q3 *What patterns in HRV can be observed in patients with PTSD?*

Q4 *How feasible is the detection of trauma signatures during trauma-specific clinical applications?*

2 Fundamentals

To be able to identify trauma and its physiological signatures, this section will provide preliminary information on underlying mechanisms of trauma and its effects on the body. A brief overview of heart rate and heart rate variability and its relation to the autonomic nervous system will be given.

2.1 Trauma: Physiological Perspective

Human emotions that arise from environmental interactions are linked to different levels of physiological arousal [AL06]. Contemporary psychological research increasingly recognizes the relationship between emotional states and physiological responses in clinical contexts [Kre10]. Therefore the motivation of this research is based on James-Lange’s Theory of Emotions, hence focuses on the physiological aspects of trauma. According to this theory, emotions are the result of perceptions of bodily changes that occur in response to physical or environmental stimuli [Can27]. Meaning that physical sensations arise first, and the interpreted emotional experience follows.

Example. When a person encounters a threatening situation, the body may respond with increased heart rate, rapid breathing and muscle tension. These physiological changes are then interpreted as fear or anxiety.

According to [Bra+01], unpleasant stimuli activates a defensive system in the body to avoid threats. The intensity of activation determines the strength of the physiological reaction. It supports the idea that emotional responses are not just single reactions, but rather *complex patterns*. The specific pattern depends on the particular emotional context and the intensity of it.

This framework provides the foundation for understanding how aversive reactions like trauma could manifest within the body through physiological responses, responses that may serve as measurable biomarkers indicative of trauma.

2.1.1 Autonomic Nervous System

The Autonomic Nervous System (ANS) is a subsystem of the human body’s peripheral nervous system [Aro+21]. It controls many vital activities and internal functions that the human is not consciously aware of doing. This includes among other things heart rate activity, respiratory rate, blood pressure and galvanic skin response [Beu+22]. The ANS itself consists of two primary branches: the sympathetic nervous system (SNS) and the parasympathetic nervous system (PNS) [McC16; Aro+21]. During psychological stress, the SNS initiates the “fight-or-flight” response, adapting the body to respond to the perceived challenge. This typically leads to an increase in heart rate [AL06].

The PNS on the other hand is responsible for the “rest-and-digest” response and typically works to restore homeostasis. Therefore it slows down heart rate and helps the body recover during periods of relative safety and relaxation.

These two systems work in opposition - when one is active, the other is suppressed. The back-and-forth between these systems is what causes rhythmic changes in heart rate and creates different levels of arousal [AL06]. However this does not mean they act completely reciprocal, instead

they function somewhat independently while still influencing each other [Beu+22]. This interplay between the SNS and PNS maintains the body’s internal balance also known as sympathovagal balance [IKK21].

A well-functioning ANS keeps this balance and contributes to overall health by supporting proper organ function, immune response, and stress management.

Generally it is said that parasympathetic effects occur much faster than sympathetic effects with the PNS being able to react in less than 1 second while the SNS usually needs more than 5 seconds to show effect [Sta03]. That is because the PNS is primarily mediated by the vagus nerve, which is the longest cranial nerve in the body and has a direct connection to the heart [CKB20].

2.1.2 General Adaptation Syndrome

Hans Selye introduced the General Adaptation Syndrome (GAS) as a model of stress to help explain the relationship between stress and illness [TY18]. This model describes how the body responds in a three-stage process when exposed to stress.

1. Alarm Reaction Stage
2. Resistance Stage
3. Exhaustion Stage

When the body is exposed to stress, it enters the alarm reaction stage where the SNS is activated and the fight-or-flight response is initiated. This is followed by the resistance stage during which the body works to recover from the initial stress response. Usually the body would be able to adapt to the stressor and would return to a state of homeostasis through parasympathetic activation. However, in case of prolonged stress, where the stressful event continues for an extended period of time until the body is unable to further cope, the body would enter the final exhaustion stage. This is where the body’s physical, emotional, and mental resources are fully depleted, leaving it completely vulnerable to illness and disease [TY18; Kim+18; CJZ20; Sel50]. This model demonstrates how stress, as a physiological and psychological reaction on the body, can be intimately linked to mental health conditions such as PTSD, further suggesting that this relationship may be quantifiable by measuring activities in the ANS.

2.2 Electrocardiogram

The electrocardiogram (ECG or EKG) represents a foundational non-invasive diagnostic tool in modern medicine that effectively records the electrical activity of the heart over time. ECG has evolved into an indispensable clinical instrument for various biomedical applications such as measuring the heart rate, examining the rhythm of heartbeats, diagnosing heart abnormalities and even recognizing emotional states [Kap+18].

This bioelectrical signal is detected through electrodes placed on the surface of the skin, which capture minute voltage fluctuations generated during cardiac muscle depolarization and subsequent repolarization processes. Each ECG lead, formed by a pair of electrodes, offers a distinct perspective

on cardiac electrical activity through views of the same heartbeat but from different electrical angles. This allows clinicians to see how electrical signals move through different parts of the heart, which helps to identify problems in specific regions. While the standard clinical practice employs a 12-lead configuration utilizing ten electrodes for comprehensive cardiac assessment, this thesis concentrates specifically on single-lead ECG applications, because the timing of heart beats are consistent across all leads. The single-lead approach, employing just two electrodes, therefore provides a simplified yet still sufficient means of monitoring heart rate activity [Cho+24].

The typical ECG waveform consists of several distinct components, each corresponding to specific cardiac events. One cycle usually includes morphological features namely P-wave, QRS-complex, T-wave, and U-wave as well as interval features such as PR-segment, ST-segment, PR interval, ST interval and RR interval [Cha+20].

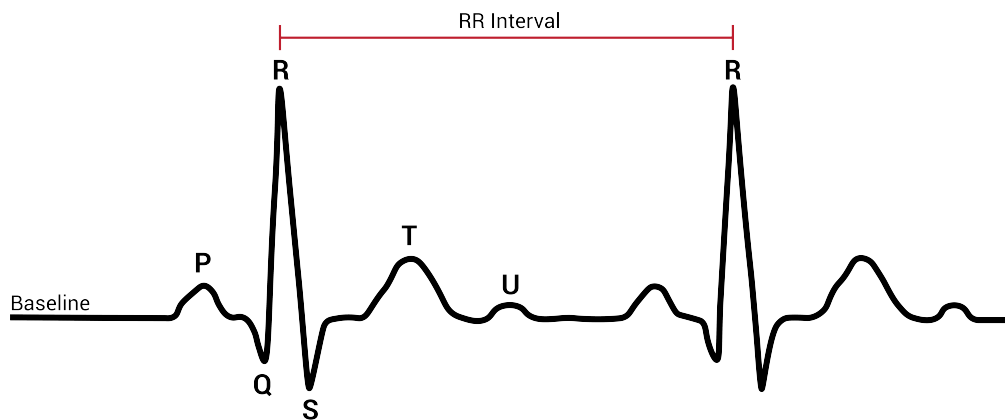


FIGURE 1: ECG of a heart in normal sinus rhythm

For this trauma research, the QRS-complex with the precise identification of R-peaks is particularly important as they serve as reference points for calculating heart rate and heart rate variability metrics.

2.2.1 Heart Rate

Heart rate (HR) represents the number of cardiac cycles per unit time, typically expressed as beats per minute (*bpm*). It serves as a physiological parameter in both clinical and research settings. The normal resting *HR* for adults can vary significantly based on many factors such as age, gender, posture, time of measurement and different physiological states [PS97; VP09; Fox+07]. Though this study indirectly implies what is considered normal by defining clinical thresholds for abnormal heart rates. This would suggest that the normal range for adults would fall between 60-100 heartbeats per minute [Ost+11], which is consistent with the findings of other population-based studies [Avr+19].

The HR can be calculated from ECG recordings by measuring the RR interval which is defined as the temporal distance between consecutive R-peaks. These peaks are typically the most prominent features in an ECG waveform [PM05].

$$\text{HR} = \frac{60}{\text{RR interval (in seconds)}} \quad (1)$$

Example. An RR interval of 0.8 seconds corresponds to a heart rate of 75 beats per minute.

The use of RR intervals form the basis for both instantaneous heart rate measurements and more complex temporal analyses such as heart rate variability.

2.2.2 Heart Rate Variability

Heart rate variability (HRV) refers to the variation in time between consecutive heartbeats also called Interbeat Intervals (IBI). Rather than the heart beating at perfectly regular intervals, there are subtle variations in timing. These variations are influenced by the ANS, which makes HRV reflective of sympathetic and parasympathetic activity. This also means it can represent how well the body is able to adjust heart rate in response to various inputs such as physical activity, emotional stress, relaxation, and more [Hon+22; GM19; Kim+18; SG17; CZ13].

HRV itself can be measured through the RR intervals of the ECG signal but once these are recorded, further in-depth metrics can be calculated using different mathematical analyses on the same set of intervals. Depending on which mathematical approach is used, metrics can be categorized into three main groups: Time-domain, Frequency-domain and Non-linear measurements. It is important to note that these measurements can also be further categorized into 24-hour, short-term (ST, ~ 5 min) and Ultra-short-term (UST, < 5 min) recordings. Measurements from different recording durations are not interchangeable, because longer recordings capture different physiological processes than shorter ones [SG17; Yug+23].

Particularly metrics that are used for ST and UST recordings will be further highlighted in this thesis, because many research has shown that shorter recordings of even under 2 minutes can still accurately measure cardiac autonomic activity [SG17; Per+17]. Typical methods for HRV analysis can effectively obtain HRV from just 3 minutes of data, when the subject remains to be stationary and stable [IKK21]. Analyzing stress within a short timeframe (ST & UST) seems to be beneficial because the body's physiological response to stress is very quick. Especially with the PNS and SNS showing activation effects in even just a couple of seconds [SG17; Weh+21].

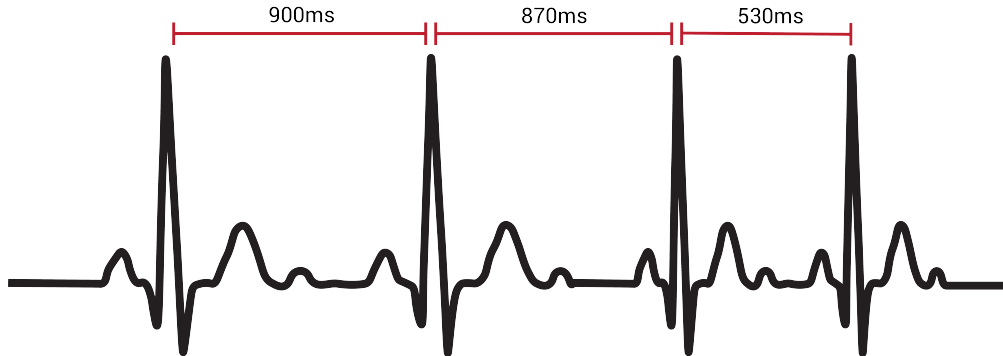


FIGURE 2: Example of heart rate variability

Each Table 1, 2 and 3 will provide a brief overview of the corresponding HRV metrics and their definitions.

Info. IBI is the general term for the time intervals between adjacent heartbeats and can refer to either RR or NN intervals. The main difference between RR and NN intervals is that RR intervals include all raw detected beats, which may include abnormal R-peaks and artifacts due to arrhythmic events or faulty sensors during measurement. NN intervals have those artifacts removed to ensure reliable and cleaner measurement of HRV [CBB12; SG17]. In this thesis however, RR will mostly be used interchangeably to keep terminology consistent and simple.

Time-domain metrics represent the temporal difference between successive heartbeats (IBIs) in their sequential form. These values are calculated directly from beat-to-beat intervals [Gul+23].

- **HR** (Heart Rate) see section 2.2.1.
- **SDRR** (Standard Deviation of all RR intervals) and **SDNN** (Standard Deviation of all NN intervals) measure both PNS and SNS activity and therefore represent global ANS function. However both parameters primarily represent parasympathetic activity when used in short-term recordings, since PNS activity is more dominant in short time scales. It is to note, in some cases it is said that *SDNN* may provide limited insight into specific ANS activity [IKK21].
- **RMSSD** (Root Mean Square of Successive RR Interval Differences) is the the primary time-domain measure used to quantify the functioning and stimulation of the vagus nerve. *RMSSD* only takes the differences between *adjacent* RR intervals into consideration and is therefore mainly used in short-term recordings. This would also imply that *RMSSD* is mainly a measure of parasympathetic activity [SG17; Yug+23; BCQ93].
- **NN50** (Number of adjacent NN intervals that differ from each other by more than 50ms)
- **pNN50** (Percentage of adjacent NN intervals that differ by more than 50 ms) closely correlates with parasympathetic activity, however *RMSSD* is generally preferred in research due to its better statistical properties [Pha+21]. Although it still may be a more reliable index than short-term *SDNN* measurements [SG17].

Parameter	Unit	Description
HR	<i>bpm</i>	Heart Rate
SDRR	<i>ms</i>	Standard Deviation of all RR intervals
SDNN	<i>ms</i>	Standard Deviation of all NN intervals
RMSSD	<i>ms</i>	Root Mean Square of Successive RR Interval Differences
NN50	—	Number of adjacent NN intervals that differ by more than 50 ms
pNN50	%	Percentage of adjacent NN intervals that differ by more than 50 ms

TABLE 1: HRV time-domain measures.

Frequency-domain metrics break down the HRV signal into its different frequency band components to see how much each band contributes to the overall signal.

- **LF** (Low Frequency) ranges between 0.04Hz and 0.15Hz and is linked to baroreceptors, which means it is influenced by both ANS branches. Some research state that it primarily represents sympathetic tone [Yug+23]. However, plenty of other research indicate that the *LF* band is not solely a measure of sympathetic activity [Pha+21]; instead, its variability reflects a combination of both parasympathetic and sympathetic activity. Despite the existing evidence suggesting that the *LF* band is not a pure indicator of sympathetic activity, many researchers still try to interpret *LF* from short-time resting ECG recordings as a direct reflection of SNS function [Gul+23].
- **HF** (High Frequency) operates between 0.15Hz and 0.40Hz and is primarily related to parasympathetic activity [Yug+23; SG17]. Reason for this is because the PNS (via the vagus nerve) modulates *HR* in real-time response to respiratory phases, creating oscillations that fall precisely within the *HF* band, which makes *HF* reliable indicator of parasympathetic activity. Furthermore, under controlled conditions where breathing happens at normal rates, the natural logarithm of *HF* (*LnHF* or *LogHF*) can be used as a way to estimate vagal tone [Pha+21; SG17; Gul+23].
- **LF/HF ratio** compares low-frequency to high-frequency power. Respectively it was assumed to reflect SNS and PNS balance, however due to the *LF* band not being a pure measure of sympathetic activity, the use of *LF/HF ratio* as a measure of sympathovagal balance has been questioned [Gul+23]. Nonetheless it remains a commonly used metric in HRV analysis [Pha+21].
- **VLF** (Very Low Frequency) band ranges from 0.003Hz to 0.04Hz and is linked to changes in vasomotor tone, which plays a role in thermoregulation and sweating through sympathetic control. As a result, changes in the external temperature can cause alterations in blood flow to the skin and therefore affect the RR interval [Yug+23]. Most research however concentrate rather on the *LF* and *HF* bands [VP09].

Parameter	Unit	Description
LF	ms^2	Low Frequency: 0.04Hz - 0.15Hz
HF	ms^2	High Frequency: 0.15Hz - 0.40Hz
VLF	ms^2	Very Low Frequency: 0.003Hz - 0.04Hz
TP	ms^2	Total Power: VLF + LF + HF
LF/HF ratio	—	Low Frequency to High Frequency ratio
HFnu	—	Normalized High Frequency
LFnu	—	Normalized Low Frequency
Log HF	—	Natural logarithm of High Frequency
Log LF	—	Natural logarithm of Low Frequency

TABLE 2: HRV frequency-domain measures.

Non-linear metrics allow to assess how random, complex, or unpredictable the HRV pattern is. HRV results from a dynamic interplay between the multiple physiologic mechanisms that constantly adjust HR. This suggests that the way HR is controlled likely involves nonlinear mechanisms that are worth to be taken into consideration [Yug+23].

- **Poincaré plot** is a scatter plot where each heartbeat interval is plotted against the previous one. The resulting pattern forms an ellipse-like shape around a diagonal line that reveals hidden patterns in the heart rhythm. Points above the line show HR slowing down, while points below show acceleration. The overall shape can indicate heart health - visually, healthy hearts create “comet” shapes while abnormal conditions produce “fan” or “complex” patterns [Pha+21].

Through Poincaré plot analysis further quantitative measures can be derived [Yug+23] [SG17]:

- **SD1** (Standard deviation perpendicular the line of identity) is shown as width of the ellipse. This measures short-term variability (equivalent to RMSSD) and reflects PNS activity.
- **SD2** (Standard deviation along the line of identity) is shown as the length of the ellipse. This captures both short and long-term variability (equivalent to *SDNN*), correlates with *LF* power and reflects both SNS and PNS activity.
- **SD1/SD2 ratio** indicates the balance between sympathetic and parasympathetic nervous systems.
- **Entropy measurements** quantify how predictable or random the heart rhythm is [Gul+23; SG17].

- **ApEn** (Approximate Entropy) measures the regularity and complexity of a time series. It quantifies how predictable a signal is by measuring pattern repetition. It works by comparing short sequences of data points and calculating how often similar patterns repeat throughout the time series. Higher entropy values generally mean more unpredictable and complex rhythms, which would relate to a healthy adaptable cardiac control, where as lower values would imply that the cardiac system is predictable and potentially pathological. both can be used as an indicator of parasympathetic activity. However it is crucial to distinguish between mere random irregularity and actual healthy complexity, as the former does not automatically imply the latter [Pha+21].
- **SampEn** (Sample Entropy) is an improved and more reliable version of *ApEn* that is less prone to overestimating regularity. *SampEn* values are interpreted similar to *ApEn* values. An advantage is that it may be more applicable to shorter time series data, even when working with fewer than 200 data points [SG17]. Both *SampEn* and *ApEn* can be used as indices of parasympathetic activity [Gul+23].

Parameter	Unit	Description
S	<i>ms</i>	Poincaré plot
SD1	<i>ms</i>	Standard deviation perpendicular the line of identity
SD2	<i>ms</i>	Standard deviation along the line of identity
SD1/SD2 ratio	–	Ratio of SD1 to SD2
ApEn	–	Approximate Entropy
SampEn	–	Sample Entropy

TABLE 3: HRV non-linear measures.

Essentially, these parameters help to quantify and analyze how *HR* changes under different conditions, making them valuable metrics for understanding physiological responses to stress, anxiety, and other emotional or physical states [GM19].

Methods on how each of these metrics are calculated will be addressed in section 4.

3 Identifying Trauma Signatures in Physiological Signals

This section aims to validate whether the proposed HRV parameters are effective in detecting stress and trauma. Furthermore, the relationship between the ANS and psychological conditions such as PTSD will be explored to reveal biomarkers and noticable patterns in HRV and ANS. Additionally, distinct experimental methodologies and their findings will be highlighted to provide a broader perspective on this field of research.

3.1 Trauma Signatures in ECG Data

As proposed through the previous sections, the ANS exhibits distinct patterns of activity that can be measured through HRV. Research has already established that parasympathetic activity is dominant under resting conditions and operates at higher frequencies (HF: 0.15-0.40 Hz), while sympathetic activity becomes dominant during stress or physical activity and operates at lower frequencies (LF: 0.04-0.15 Hz) [Moo+13; Raj+06].

When experiencing stress from various sources such as deadlines, exams, or financial worries, the SNS activates. This activation triggers cortisol release and prepares the body for rapid response to perceived threats. The physiological response of that results in overall reduced HRV values and increased activity in the lower frequency band of the heart rhythm [IKK21].

The most commonly reported reason for changes in HRV was reduced parasympathetic activity. This reduction is identified by a drop in the LF and HF component as well as a rise in the LF/HF ratio. A significant decrease is also very common in $SDNN$, $RMSSD$ and $pNN50$ measurements [Kim+18; Per+17; Arz+15; Han+25]. According to these studies, LF tends to rather decrease under stress conditions. This reduction though is not always statistically significant when comparing stressed and non-stressed periods [Per+17]. It confirms the strong parasympathetic influence in the LF band as suggested in the previous section.

The increase in the LF/HF ratio however, implies a greater sympathetic outflow during stress than at rest [DM21].

Non-linear metrics, though not often, have been explored in relation to stress as well, revealing several correlations. One study investigating these measures found that $SD1$, which reflects short-term HRV like $RMSSD$, decreased with stress, indicating an inhibition of parasympathetic activity. $SD2$ also decreased under stress, since it reflects both ANS branches equivalent to $SDNN$ [Per+17].

$SampEn$ showed lower values with higher stress levels, suggesting a reduction in the complexity or unpredictability of physiological signals during stressful periods. However, it is important to note that the research raised theoretical concerns about SampEntropy’s reliability, particularly concerning its sensitivity to input parameters and data length, which can affect its consistency and interpretation [Per+17]. In that study specifically, parameters were calculated using a UST recording of 50 seconds, which proved here to be very effective for stress detection.

Generally, a blockage in parasympathetic activity substantially decreases both Entropy measures, $ApEn$ and $SampEn$, showing these to be viable indicators of parasympathetic activity overall [Gul+23].

Specific Findings in PTSD Populations have consistently shown that people with Post-Traumatic Stress Disorder, as well as those who have endured significant trauma and trauma-related stress, display unique cardiac patterns also. Specifically, they tend to have reduced parasympathetic activity and increased sympathetic activation. These changes are evident in their altered HRV parameters [IKK21]. Meta-analytic research has demonstrated clearly that individuals with PTSD show consistently lower HRV compared to healthy controls, both at rest and during induced stress phases. Specifically, studies have found reductions across multiple short-time HRV measures, including *RMSSD*, *HF*, *LF* and *SDNN*. The *LF/HF ratio* on the other hand often showed an increase, again indicating altered sympathovagal balance through a dominance of sympathetic activity and reduced parasympathetic action [SS20; IKK21; Per+17]. These results were even present when analyzed on 24h recordings [Ami13], which seems to be plausible, given the long-term nature of PTSD.

Furthermore, Sympathetic stimulation tends to increase *HR* where as parasympathetic stimulation slows down the *HR*. [Sta03].

The HR adapts or responds to both physical and emotional conditions. Specifically, researchers observed subjects under stress and relaxation. They found that as stress increased, *HR* did also and the other way around, confirming a correlation between a distressed emotional state and physiological response [Dal+24; Mul+12; Kim+21].

Recent Studies and meta analyses have further confirmed that acute mental stress triggers *HR* to increase as well [VP09; Hua+13]. But especially when stress is induced to individuals that suffer from PTSD, *HR* increases significantly due to higher SNS activity [SS20].

HRV itself is also influenced by a logical phenomenon called “cycle length dependence” which proposes an inverse relationship between HR and HRV. A rise in *HR* leaves less time for variability between beats which consequently lowers HRV. Conversely, a slower HR provides more time between beats, allowing for greater IBI variation and thus increases HRV [SG17]. This alignes with the above findings that have shown increased *HR* alongside with decreased HRV values among stressed individuals and patients with PTSD.

The severity of PTSD symptoms correlates with the degree of autonomic impairment - more severe PTSD was associated with greater reductions in HRV. Importantly, patients whose PTSD had resolved (remitted PTSD) showed mostly normal autonomic function, suggesting that these negative effects may be reversible when PTSD symptoms improve [Ami13].

Info. Stress and trauma is typically associated with reduced HRV. A reduction in HRV refers to decreased values in *SDNN*, *RMSSD*, *pNN50*, *LF*, *HF*, *TP*, *SD1* and *SD2* as well as increased values in *HR* and *LF/HF ratio*.

3.2 Distinct Experimental Studies

There are plenty of experimental studies regarding stress but they often differ in terms of how stress is being induced, and what type of patients are studied. For example, individuals experiencing depression or anxiety disorders or even untreated patients with schizophrenia often exhibit lower HRV as well, showing similar ANS disfunction due to their inherent relationship [Nay+23]. Exploring these methodologies could give even further insight into general mental illness and phys-

iological response, rather than just focusing on PTSD alone. It also backs up the use of certain HRV parameters as potential indicators of mental health conditions.

HRV in psychiatric disorders. One study compared HRV measurements between patients with four psychiatric disorders (schizophrenia, bipolar disorder, PTSD, and major depressive disorder) and healthy controls [Moo+13]. While they are distinct psychiatric conditions, they still share a close relationship with one another, having overlapping symptoms and causes. For instance, traumatic events may induce PTSD and can significantly increase the risk of developing trauma-related depression [Wan+23]. Findings in ST recordings of 5 minutes show: Individuals with schizophrenia exhibited significantly reduced *SDNN* and *HF* compared to healthy controls.

These findings suggest dysfunctional parasympathetic activity alongside relatively preserved sympathetic function in this population. Of all the disorders studied, bipolar disorder showed the most pronounced HRV dysfunction. Patients with bipolar disorder had significantly reduced *SDNN*, *RMSSD*, *TP*, *LF*, and *HF* when compared to healthy controls. Interestingly, this particular study found no significant main changes in HRV in individuals with Major Depressive Disorder. This finding contrasts with some previous research that has reported reduced HRV in depression [Lin+19].

Patients with PTSD demonstrated significantly reduced *HF* compared to healthy controls, pointing out yet again decreased parasympathetic activity and potentially inflexible response regulation in individuals with PTSD in general.

Throughout the study, *HF* power was the most consistently affected measure across all disorders. This suggests that parasympathetic dysfunction is a common feature across all of these psychiatric conditions. The researchers advocate that while HRV (particularly *HF*) appears sensitive to psychiatric illness in general, it may not be specific enough to discriminate between different psychiatric disorders. However, it could still potentially serve as a supplementary tool to differentiate between psychiatric patients and healthy individuals [Moo+13].

It is to note that HRV alone cannot diagnose specific mental illnesses or diseases.

HRV as a mental state indicator. Current mental stress evaluation faces challenges such as, no single clear judgment standard exists, researchers typically must observe multiple HRV indicators and no individual parameter (time-domain, frequency-domain or non-linear) can accurately represent mental stress changes alone [Luo+22]. To address these challenges, [Luo+22] proposed using a body pressure index to allow individuals to intuitively understand their mental stress status. This index is based on a mathematical model that quantifies mental stress rather than relying on subjective judgment, using time-domain and frequency-domain parameters: *SDNN*, *pNN50*, *HR* & *TP*, *HF*, *LF/HF ratio*. To validate the proposed mental state (MS) measurement model, two distinct experiments were conducted. These experiments were designed to assess the model’s capability to detect and quantify changes in psychological and physiological stress levels under different conditions. The first experiment examined the impact of physical exercise on mental states, while the second investigated the effects of environmental stimuli using virtual reality, where participants had gone through two phases: Relaxation Phase: Subjects were first exposed to soothing landscape

videos in a virtual reality environment while baseline MS measurements were recorded. Stress Induction Phase: Subsequently, the same subjects were placed alone in darkened rooms and shown horror movie clips, after which MS measurements were again recorded.

During exposure to calming landscape videos, subjects exhibited minimal psychological and physical stress, with average MS values on the established scale. Following exposure to horror film clips, MS values increased significantly, with all subjects showing increases generally exceeding 60%. The most pronounced individual response showed an MS value increase of 106.7%, representing more than a doubling of the measured stress level.

The results confirmed that the MS measurement model successfully captured the stress response induced by physical exercise as well as environmental stimulus. The observed increases in MS values aligned with expected physiological responses, providing initial validation for the model’s sensitivity to exercise- and psychologically-induced stress [Luo+22].

Similarly, established commercialized software for HRV analysis such as KubiosHRV¹ use a similar approach to assess mental stress through the use of a PNS and SNS index. Their PNS index is calculated using metrics such as the mean RR interval, *RMSSD* and *SD1*. On the other hand the mean *HR*, the Baevsky’s Stress Index and *SD2* are being used to calculate the SNS index.

HRV in impaired cardiovascular recovery. Another research studied 321 people who had recently experienced myocardial infarctions (heart attacks) [Kim+20]. They wanted to understand whether those who experienced significant trauma in early life would have different ANS responses - particularly how their hearts handle stress and recover afterward. The participants underwent a controlled stress test (giving a speech) while researchers monitored their HRV. They measured HRV at three time points: At rest (baseline), during the stressful speech task and during recovery after the stress phase. Early-life trauma was assessed using a validated questionnaire, with participants classified as having either high or low trauma exposure based on their scores. The study revealed an important pattern in the recovery phase. While there were no differences between high-trauma and low-trauma groups during baseline or active stress response, a significant difference emerged during recovery: People with high early-life trauma exposure showed *impaired recovery* - their HRV remained disrupted longer after the stress ended, while those with low trauma exposure returned to normal baseline levels more quickly, signifying reduced and weakened PNS activity. This highlights how psychological trauma experienced early in life can have measurable, long-lasting effects on physical health, specifically cardiovascular function under stress [Kim+20].

¹ <https://www.kubios.com/blog/hrv-ans-function/> (last accessed 08/15/2025)

4 ECG Signal Processing and Feature Extraction

ECG signals are inherently prone to noise and artifacts from multiple sources. Effective signal processing is therefore essential for accurate HRV parameter extraction. This section provides deeper insight into how HRV metrics are obtained. This includes an outline of processing methods used to clean and prepare ECG data for HRV analysis.

Signal Processing methods are very complex and there is an extensive amount of literature about such different kinds of methods [Anb+23]. Which is why for this research only the most common and effective methods will be used and highlighted.

To ensure the HRV features extracted are accurate and reliable, all proposed steps of signal processing will be applied to an open sourced example ECG. The signal is a five-minute segment from lead MLII of record 208 in the MIT-BIH Arrhythmia Database, made available through PhysioNet and python’s scipy library². It showcases a range of cardiac activity, including normal heartbeats, disease-related alterations, and noise-induced distortions.

4.1 Signal Preprocessing

Signal preprocessing is vital for ECG analysis, as it eliminates noise and artifacts that hinder accurate feature extraction. Previous work has also consistently ascertained that preprocessing has positive influence on HRV analysis [Weh+21]. This thesis will concentrate on preprocessing steps that are particularly important for R-peak detection, as processing the signal excessively may lead to filtering out valuable information which could result in inadequate, less efficient output and representation of HRV activity associated with stress [IKK21].

When working with raw ECG data, typically there are two main types of artifacts: technical artifacts and physiological artifacts [Kap+18; Sal+22].

Technical Artifacts. These arise from external sources or equipment and include:

- *Power line interference:* Electrical noise from AC power lines.
- *Baseline wander:* Slow, low-frequency shifts in the ECG baseline.
- *Muscle artifacts:* Electrical signals generated by muscle movement.
- *Instrumentation noise:* Random noise, often Gaussian, originating from the recording equipment.

Physiological Artifacts. These originate from the body itself, such as:

- *Ectopic beats:* Irregular heartbeats that originate outside the sinoatrial node. This category includes premature atrial contractions and premature ventricular contractions, which causes irregularities in data. While these can be observed and addressed in HRV data through either manual review or automated techniques, existing preprocessing methods for HRV have significant limitations.

² <https://docs.scipy.org/doc/scipy/reference/generated/scipy.datasets.electrocardiogram.html> (last accessed 08/15/2025)

Current approaches to cleaning ECG data and preparing it for HRV analysis face **several challenges**:

- Most methods have a limited scope, since they mostly target only a single type of noise.
- There is not one widely accepted or consistent approach for HRV preprocessing.
- Manual artifact removal can be time-intensive and prone to human error.
- The common practice of simply deleting ectopic beats can lead to a systematic loss of valuable physiological information.
- Many current methods inadvertently alter and distort the original ECG signal, potentially impacting the accuracy of subsequent analyses.

In general HRV analysis, preprocessing steps are often kept to a minimum because the focus is on the RR intervals rather than the exact morphology of individual ECG waveforms.

To address technical artifacts, many researchers mainly use denoising as a preprocessing step for classification and disease detection [Anb+23].

However research indicates that for analyzing ECG signals and detecting fiducial points like R peaks, the most effective technique involves using high-pass and low-pass or some sort of band-pass filtering [Isr+05; SNP24; Kap+18; Esg+22].

Info. A bandpass filter is a combination of low-pass and high-pass filter that allows signals within a certain frequency range to pass through while attenuating frequencies outside that range. In ECG they are typically used to remove low-frequency noise (e.g. baseline drift) and high-frequency noise (e.g. muscle artifacts) [Anb+23].

Often times to remove power line interference, studies use a notch filter, which is a type of bandstop filter that removes a specific frequency (mostly set to 50Hz) without affecting the rest of the signal [Kap+18].

Ectopic beats can introduce a bias into HRV results, making it difficult to accurately interpret those [Per+17]. Regarding the removal of these physiological artifacts, there is no clear consensus or recommendations in literature on the most appropriate methods for detecting and correcting doubtful heartbeats [Gal+21].

Nonetheless to prevent misidentification of extra or premature R peaks caused by physiological artifacts, usually thresholds can be applied to eliminate those peaks using: previous RR interval durations and last R-peak amplitudes [SNP24; Per+17]. These adaptive thresholding techniques dynamically adjust the detection criteria for R-peaks. They achieve this by using the amplitude of the most recently detected R-peak (or an average of the last few) to set a flexible threshold for identifying the subsequent R-peak. The same principle can be applied to RR interval durations.

Example. If the last R-peak had an amplitude of 1.0 mV, the threshold for the next R-peak might be set as a percentage (e.g., 60-80%) of the last R-peak's amplitude. This means that the next R-peak must exceed 0.6 mV to be considered valid.

One study identified the Butterworth filter as the optimal choice for removing noise from ECG signals when analyzing HRV metrics. The filter showed particularly strong performance in ac-

curately detecting R-peaks, surpassing alternative approaches including Fast Fourier Transform, wavelet filtering, and Chebyshev filtering techniques. Based on the research findings, the Butterworth filter outperformed other methods in processing cardiac electrical signals and deriving HRV parameters. The researchers also examined a 5th-order Butterworth filter to have the highest signal-to-noise ratio (1.1 - 34.4 % larger) and the smallest percent root-mean-square difference (15.2 - 66.1 % smaller) compared to other orders, which indicates superior signal processing performance [Ren+24].

The use of a Butterworth bandpass filter has shown to be quite common and useful in many other studies as well [Anb+23]. Especially when used for R-peak detection it provided reliable ECG data with high accuracy and minor error rates [Hus23; Liu+17].

Info. A Butterworth bandpass filter is essentially a specific implementation of a bandpass filter using Butterworth design principles. It is characterized by a maximally flat frequency response in the passband. Meaning there are no ripples or variations in gain within the frequency range that is supposed to be preserved. It has also a monotonic rolloff in both stopbands. The rolloff rate is determined by the filter order where a steeper rolloff is achieved with higher order. There is no unified order that can be used for all ECG signals, as the optimal order depends on the specific characteristics of the signal being processed.

An example of how preprocessing can affect the an ECG signal is shown in Fig...

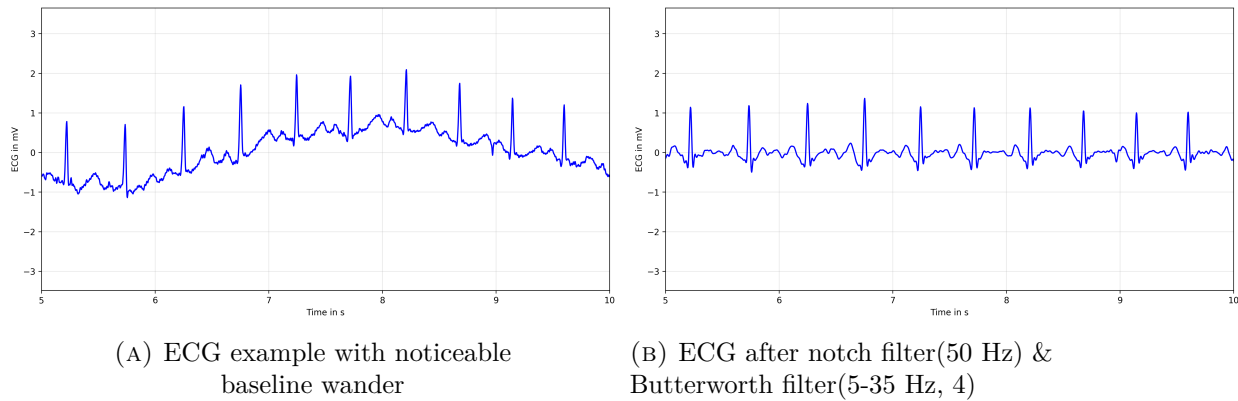


FIGURE 3: Preprocessing example

4.2 R-Peak Detection

After filtering the signal, a proper R-peak or QRS-complex detection algorithm must be applied to precisely identify true R-peaks in the ECG signal.

For this, a study compared three R-peak detection algorithms: Pan-Tompkins, Wavelet-based, and Hilbert transform. Additionally, compared the HRV features extracted from the detected R-peaks.

The Hilbert Double Envelope Method (HDEM) algorithm, which is based on the Hilbert transform, emerged as the best overall performer for R-peak detection when compared to Pan-Tompkins and Wavelet-based methods. However when comparing HRV parameters derived from algorithm-

detected peaks versus manually verified “gold standard” measurements: All algorithms produced statistically equivalent results such that no significant differences were found between the derived HRV parameters relative to the ground truth values [Esg+22].

Moreover, given the amount of research that has been done, the most common technique for QRS detection is the one proposed by *Pan and Tompkins*. It is one of the most widely accepted and highly validated algorithms, serving as a benchmark for many other R-peak detection methods not only for ECG in general but also for HRV specifically [Gal+21]. This means its performance is well-understood, and there are many implementations and resources available. With accurate clinical ECG signal data, this approach offers good detection performance. However, in very low-quality and noisy signals, as well as ambulatory ECG recordings, the Pan-Tompkins algorithm may struggle to maintain its accuracy. That is why researchers propose modifications to the algorithm to improve its performance in noisy environments and overall. A modification can for example be a change of the filtering method to a better performing one, such as the Butterworth filter. The original Pan-Tompkins bandpass filter is actually implemented as a cascade of a low-pass and high-pass filter, so that replacing it with a butterworth bandpass would be conceptually similar. Experimental results even show improved versions do perform noticeably better for both R-peak detection and even execution time [IK22; Liu+17].

By accurately identifying R-peaks, it provides the precise RR intervals needed for reliable HRV calculation. HRV analysis software such as PhysioNet [Moe20] or (even commercialized) like KubiosHRV³ as well as research studies use Pan-Tompkins or at least an optimized version of it as their R-peak detection algorithm of choice [IK22].

As detailed in Figure 4, the algorithm operates in three main stages [Ren+24; RAO24]:

1. **Signal Pre-processing:**

The initial step involves taking the raw ECG signal and denoising it to remove any unwanted interference. The standard algorithm mostly uses a simple bandpass filter with a bandwidth of 5-15 Hz.

2. **Signal Processing:**

Signal pre-processing could introduce signal distortion, potentially leading to the misidentification of non-R peaks as R peaks. To mitigate this, the algorithm performs a derivative step on the output signal. This step minimizes the impact of P and T waves on the R waves. The derivative output is then squared, which highlights the high-frequency components of the QRS wave group. Following this, moving window integration is applied. This step eliminates the characteristics of all other waveforms (like P, Q, S, and T waves), leaving primarily the R waves. This process helps to smooth out the signal further, enhancing the width and slope of the QRS complex.

3. **R-peak Localization:**

Finally, the algorithm employs adaptive thresholds to accurately locate the R-peaks within the processed signal.

³ <https://www.kubios.com/blog/beat-detection-and-hrv-time-series> (last accessed 08/15/2025)

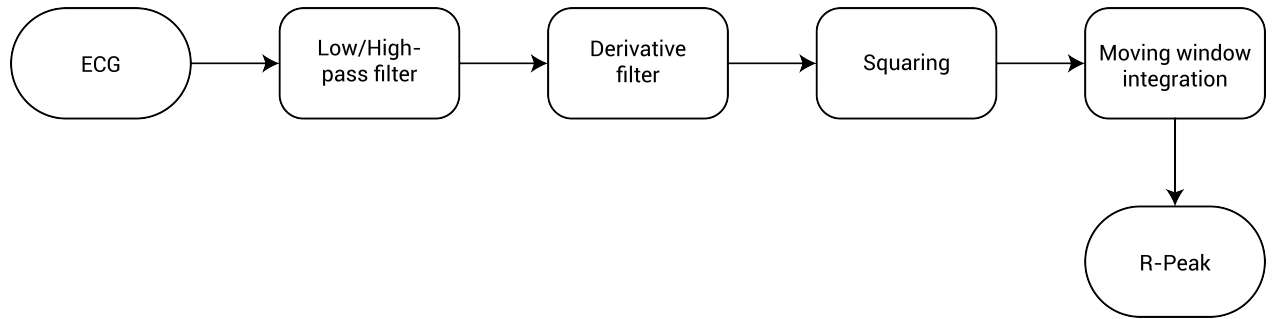


FIGURE 4: Pan-Tompkins algorithm diagram

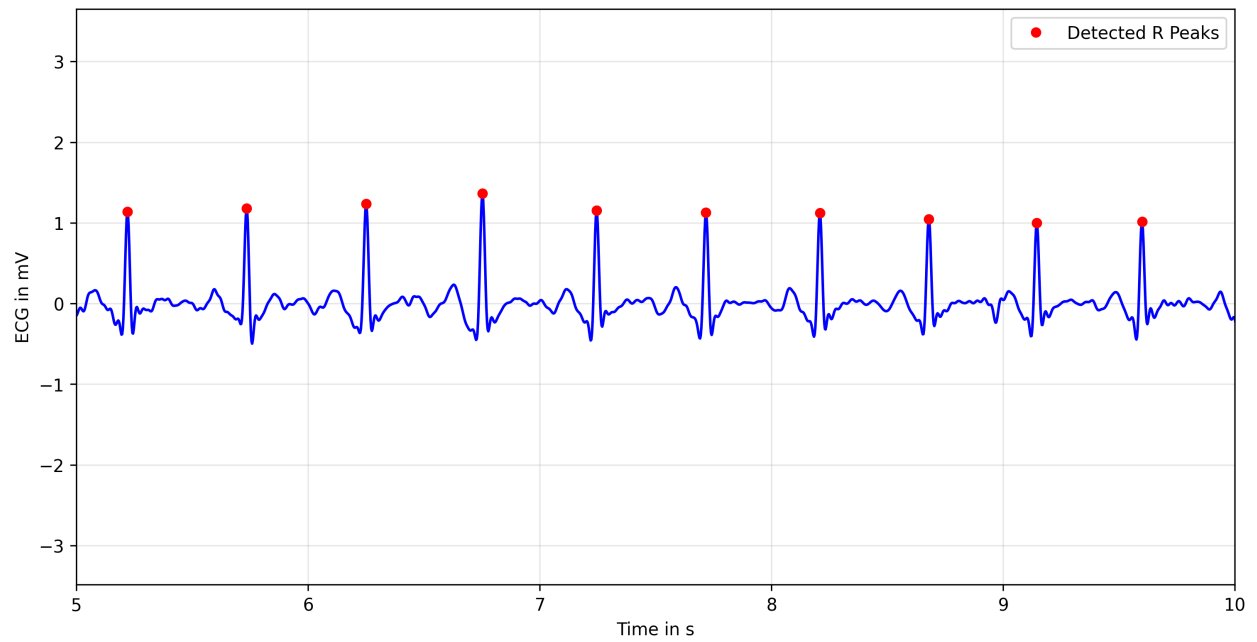


FIGURE 5: R-Peak detection using Pan Tompkins algorithm

4.3 Time-Domain Analysis

After preprocessing and R-peak detection, the RR intervals can be extracted and used to calculate time-domain indices with the following formulas:

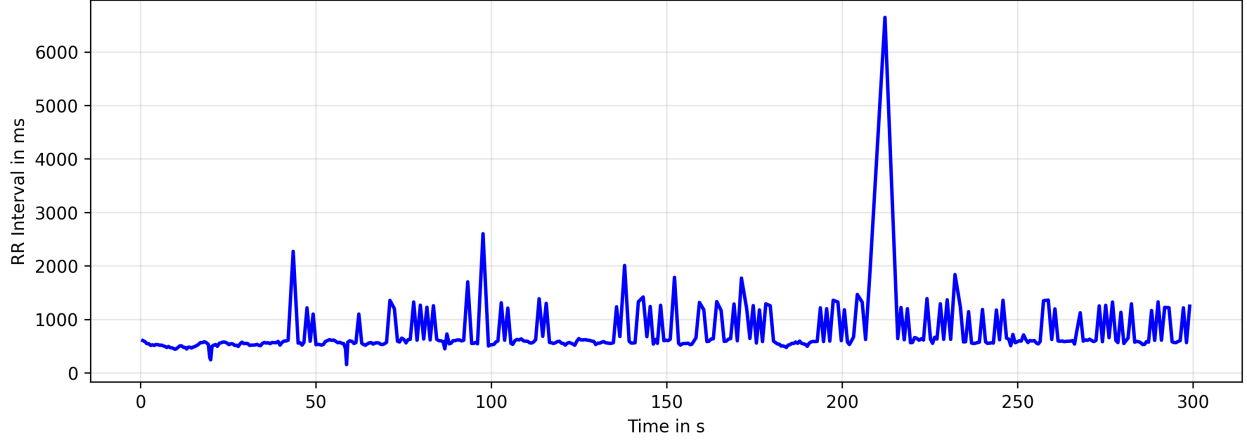


FIGURE 6: RR interval plot example with noticeable outlier

$$HR = \frac{60}{RR} \quad (2)$$

where:

HR : Heart rate in $[bpm]$

RR : RR interval in $[s]$

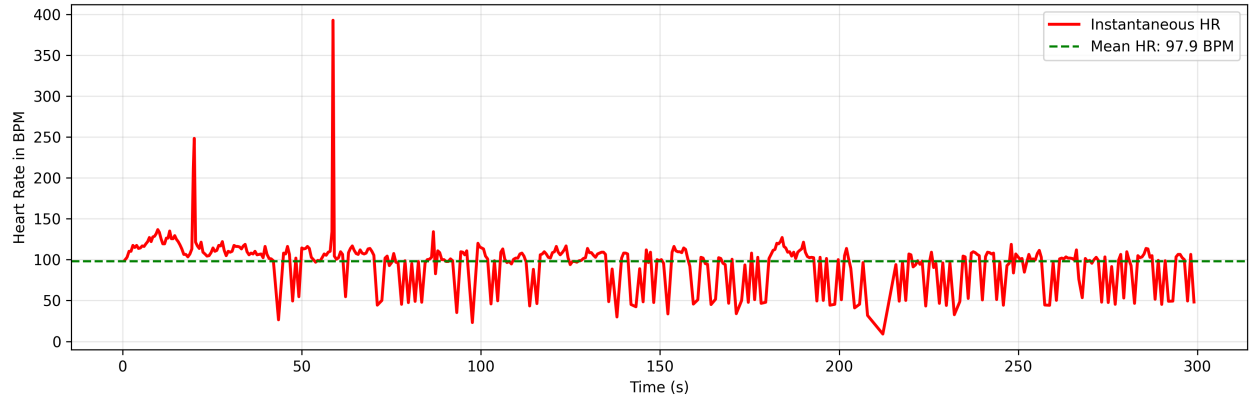


FIGURE 7: Instantaneous heart rate example

$$SDNN = \sqrt{\frac{1}{N-1} \sum_{i=1}^N (RR_i - \overline{RR})^2} \quad (3)$$

where:

$SDNN$: Standard Deviation of all RR intervals in $[ms]$

N : Total number of RR intervals

RR_i : RR interval at index i in $[ms]$

$\overline{RR}$: Mean of all RR intervals in $[ms]$

$$RMSSD = \sqrt{\frac{1}{N-1} \sum_{i=1}^{N-1} (RR_{i+1} - RR_i)^2} \quad (4)$$

where:

$RMSSD$: Root Mean Square of the Successive RR intervals Differences in $[ms]$

N : Total number of RR intervals

RR_i : RR interval at index i in $[ms]$

$$NN50 = \text{Count of } |RR_{i+1} - RR_i| > 50 \quad (5)$$

where:

$NN50$: Number of successive RR interval pairs that differ by more than $50ms$

RR_i : RR interval at index i in $[ms]$

$$PNN50 = \frac{NN50}{N} \cdot 100 \quad (6)$$

where:

$PNN50$: Percentage of pairs of successive RR intervals that differ by more than $50ms$

$NN50$: Number of pairs of successive RR intervals that differ by more than $50ms$

N : Total number of RR intervals

4.4 Frequency-Domain Analysis

Frequency-domain analysis transforms the RR interval time series into frequency components, revealing the power distribution across different frequency bands.

First, the R-R interval time series undergoes preprocessing, including resampling to create evenly spaced data points (resampled to a uniform sampling rate) (typically 2-4 Hz) and detrending to remove low-frequency trends like slow baseline drift. Next, spectral analysis is performed using specific algorithms to generate the power spectral density (PSD). Finally, power calculations are made by integrating the power spectral density within each frequency band [Nay+23; IKK21].

When calculating the PSD for HRV, two main categories of methods are used: non-parametric and parametric. Non-parametric methods like the Fast Fourier Transform (FFT), Welch’s method or the Lomb-Scargle periodogram are straightforward to compute quickly and don’t require any prior assumptions about the signal’s underlying structure. In contrast, parametric methods, such as Autoregressive (AR) model offer smoother spectral components and accurate PSD estimates even with smaller data sets. However, they rely on choosing appropriate parameters and assuming the data fits a specific signal model. A key challenge with parametric methods is determining the correct model order, which varies depending on the ECG duration, meaning there’s no single ideal setting that works for all situations [GM19].

The method used to estimate the PSD can differ between studies. Traditionally, the FFT has been employed for this purpose. However, a significant drawback of classical methods like the FFT is spectral leakage. This occurs because real-world data must be “windowed” or truncated to a finite length, which can cause energy from strong frequency components to “leak” into adjacent frequencies, weak signals to be masked or hidden by this leakage and reduce accuracy in identifying subtle frequency components in HRV data. To overcome these limitations, parametric methods, such as the AR model, are often preferred. AR models offer superior spectral analysis compared to FFT-based methods, while remaining computationally efficient due to their ability to estimate parameters by solving relatively simple linear equations [SG17; Raj+06].

A significant challenge in general research utilizing frequency-domain analysis is the inconsistency of results across various methodologies. Different spectral analysis algorithms, such as the FFT and the Lomb-Scargle method, often yield disparate outcomes, making it difficult to compare findings between studies. For instance, the FFT frequently inflates the LF/HF when compared to the Lomb-Scargle method. Even when the same algorithm is employed, the results can fluctuate considerably depending on parameter selections like window length or model order.

To address this issue, normalization is recommended as a solution. This involves dividing each frequency component by the total power, generating normalized versions ($LFnu$ and $HFnu$). These normalized values are less susceptible to variations caused by methodological discrepancies or shifts in overall HR power. Consequently, guidelines suggest reporting both absolute values (LF , HF) and their normalized counterparts ($LFnu$, $HFnu$) to ensure a comprehensive analysis [Pha+21].

For this thesis, the Welch’s method will be primarily used to calculate the PSD. It is a non-parametric method that is based on the FFT. Welch’s method divides the data into overlapping segments, applies FFT to each segment and averages the results, which reduces noise and provides

more reliable frequency analysis. This produces the following periodogram:

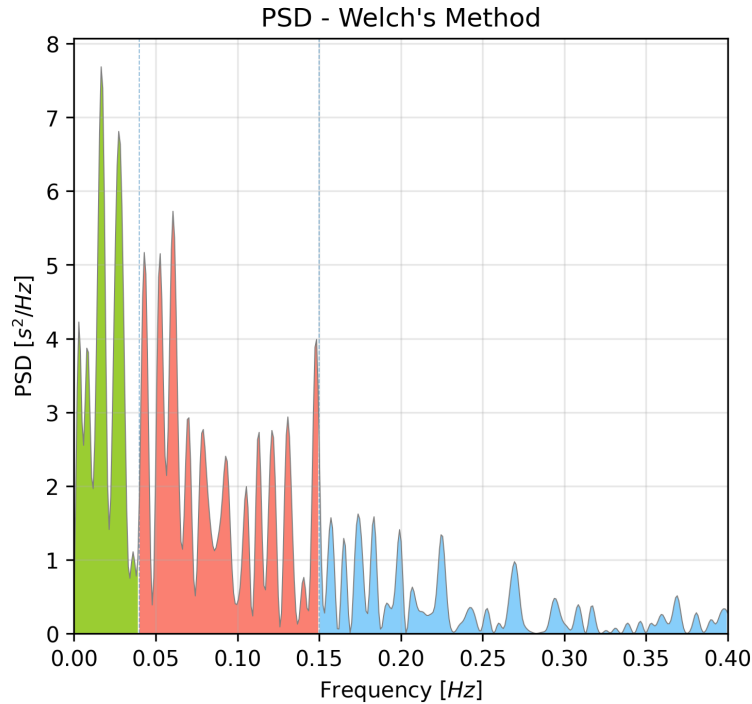


FIGURE 8: Power Spectral Density example using Welch's method

For each band, the power is then calculated by integrating the power spectral density in the specific frequency range:

$$\text{Power} = \int_{f_1}^{f_2} \text{PSD}(f) df \quad (7)$$

where:

f_1 : Lower frequency limit of the band

f_2 : Upper frequency limit of the band

$\text{PSD}(f)$: Power spectral density over the specified frequency range f

4.5 Non-linear Analysis

When studying HRV, researchers every so often look at nonlinear parameters to better understand the complex and unpredictable ways the human body's physiology influences heart rhythms. While various mathematical approaches exist for this type of analysis, many are too complicated or lack sufficient scientific support for effective HRV analysis. Consequently, only a few nonlinear methods are regularly being used in HRV research [GM19]. Especially when utilized in studies with a focus on psychological stress and trauma, nonlinear derived parameters are underrepresented. Nevertheless, when made use of, common methods include metrics derived from Poincaré plots and Entropy.

Poincaré Plot is constructed by taking each RR interval and plotting it against the immediately following interval. If there is a sequence of intervals $RR_1, RR_2, RR_3, RR_4 \dots$, points would be plotted at coordinates (RR_1, RR_2) , (RR_2, RR_3) , (RR_3, RR_4) and so on. The example ECG produces the following plot:

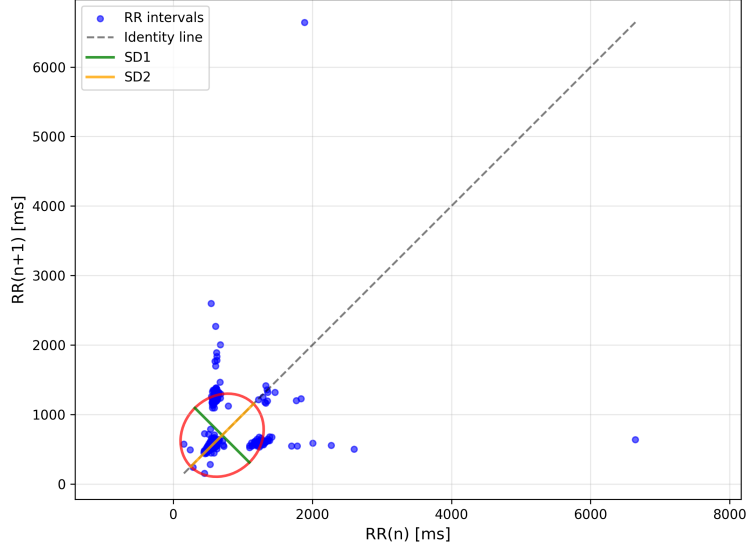


FIGURE 9: Poincaré Plot example

Info. There are different ways on how $SD1$ and $SD2$ can be calculated. The following equations use the time-domain measure $SDSD$ (Standard deviation of successive differences) metric, which essentially yields identical results as $RMSSD$ when applied to stationary time series [BPK01; GM19].

$$SDSD = \sqrt{\frac{1}{N-1} \sum_{i=1}^{N-1} (RR_{i+1} - RR_i)^2} \quad (8)$$

where:

$SDSD$: Standard deviation of successive differences in $[ms]$

N : Total number of RR intervals

RR_i : RR interval at index i in $[ms]$

$$SD1 = \sqrt{\frac{1}{2} \cdot SDSD^2} \quad (9)$$

where:

$SD1$: Standard deviation of the Poincaré plot perpendicular to the line of identity

$SDSD$: Standard deviation of successive differences in $[ms]$

$$SD2 = \sqrt{2 \cdot SDNN^2 - \frac{1}{2} \cdot SDSD^2} \quad (10)$$

where:

$SD2$: Standard deviation of the Poincaré plot along the line of identity

$SDNN$: Standard Deviation of NN intervals

$SDSD$: Standard deviation of successive differences in $[ms]$

5 Existing Tools

In recent decades, a growing number of new Heart Rate Variability (HRV) measurement tools and their accompanying software have emerged such as previously mentioned KubiosHRV⁴ or also the Oura Ring⁵, WHOOP Strap⁶, Garmin Watches⁷ and many more. However, the software for most of these tools are closed-source, meaning they come with expensive licenses or proprietary algorithms, that restrict developers from accessing their source code. This significantly limits the ability to create custom applications and improve upon them. While open-source HRV solutions exist, they often suffer from their own drawbacks, including limited features, unvalidated results, or a lack of comprehensive support for common programming languages. [GMP19]

This section provides an brief overview of some existing tools and libraries for HRV analysis. Mostly focusing on python open-source solutions, since they are accessible for developers and easy to integrate into custom workflows. There will be example code given for each tool, demonstrating ease of use and functionality. Given the significance of evaluation, the tools will be compared with each other based on their metric calculations and usability.

5.1 BioSPPy

BioSPPy (BioSignal Processing in Python)⁸ is a open-source Python library, that provides end-to-end processing capabilities for physiological data collected from devices like smartwatches, medical equipment, or research instruments. BioSPPy handles multiple biosignal types including ECG (heart), EEG (brain), EMG (muscle), EDA (skin conductance), PPG (blood volume). Since its launch in 2015, BioSPPy has demonstrated its substantial impact through numerous downloads and citations in scientific literature. Popular libraries like NeuroKit2 and pyHRV are originally built upon BioSPPy. It essentially serves as a foundational tool in the physiological signal processing field by providing a comprehensive, accessible, and well-documented toolbox that eliminates the need for researchers to build processing pipelines from scratch, thereby accelerating research and development in biomedical applications. [Bot+24]

Particularly for HRV analysis, BioSPPy offers a range of features including, ECG signal processing techniques, R-Peak detection algorithms and a specific HRV submodule that calculates various HRV metrics.

Example.

```
1 from biosppy.signals import ecg, hrv
2
3 # Load ECG signal
4 signal = biosppy.signals.ecg.load_ecg("path_to_ecg_file")
5
6 # Extract R-peaks
```

```
4 https://www.kubios.com (last accessed 08/15/2025)
5 https://ouraring.com/ (last accessed 08/15/2025)
6 https://www.whoop.com (last accessed 08/15/2025)
7 https://www.garmin.com (last accessed 08/15/2025)
8 https://github.com/PIA-Group/BioSPPy/ (last accessed 08/15/2025)
```

```
7 processed = ecg.ecg(signal=signal, sampling_rate=1000, show=False)
8 rpeaks = processed['rpeaks']
9
10 # Calculate RR intervals
11 rr_intervals = np.diff(rpeaks) / sampling_rate * 1000
12
13 # Calculate HRV metrics
14 hrv_results = hrv.hrv_timedomain(rr_intervals)
15
16 # Print HRV metrics
17 print("RMSSD:", hrv_results['rmssd'])
```

5.2 NeuroKit2

NeuroKit2 [Mak+21] a versatile and community-driven Python library designed for processing a wide range of physiological signals (e.g., ECG, PPG, EDA, EMG, RSP). It offers a uniform application programming interface for both experienced and novice programmers. The library provides a comprehensive set of functionalities, including signal simulation, data management, event and epoch extraction and various signal processing techniques like filtering, resampling and rate computation. NeuroKit2 emphasizes reliability and trustworthiness, incorporating peer-reviewed processing pipelines and offering validated analysis pipelines that users can customize themselves. The implementations of pipelines and algorithms have been tested against many established open-sourced software such as BioSPPy [Bot+24], hrv [BP20] and HeartPy [Van+19].

Example.

```
1 import neurokit2 as nk
2
3 # Load ECG signal
4 ecg_signal = nk.data("path_to_ecg_file")
5
6 # Process ECG
7 _, rpeaks = nk.ecg_peaks(ecg_signal, sampling_rate=1000)
8 r_peaks_indices = rpeaks['ECG_R_Peaks']
9
10 rr_intervals = np.diff(r_peaks_indices) / sampling_rate * 1000
11
12 # Calculate HRV metrics
13 hrv_metrics = nk.hrv(rr_intervals, sampling_rate=1000)
14
15 # Print HRV metrics
16 print("RMSSD:", hrv_metrics['RMSSD'])
```

5.3 pyHRV

pyHRV⁹ is a fully open-source Python toolbox designed for heart rate variability (HRV) analysis in custom research and development. This toolbox has been validated against previous mentioned

⁹ <https://github.com/PGomes92/pyhrv> (last accessed 08/15/2025)

Kubios HRV, which is considered to be the gold-standard software in this field. pyHRV calculates a comprehensive set of 78 HRV parameters, encompassing time-domain (23), frequency-domain (48), and non-linear (7) measures. For validation, they analyzed 50 short-term (5-minute) and 50 long-term (60-minute) Normal-to-Normal Interval (NNI) series. The comparison revealed that most HRV metrics calculated through pyHRV, especially the ones needed for this research, yielded acceptable results compared to Kubios. With some parameters being identical to the gold-standard and others only showing marginal or negligible differences, indicating good agreement overall. It is to be noted that only the Welch’s method was sufficient for frequency-domain analysis, as the Lomb-Scargle and Autoregressive method displayed significant differences, suggesting they require further investigation and refinement [GM19; GMP19].

Example.

```

1  import pyhrv.time_domain as time_domain
2
3  # Load ECG signal
4
5  # R-Peak detection
6
7  # Calculate HRV metrics
8  hrv_metrics = {}
9  hrv_metrics['time_domain'] = time_domain.calculate(rr_intervals, sampling_rate=1000)
10
11 # Print HRV metrics
12 print("RMSSD:", hrv_metrics['time_domain']['RMSSD'])

```

5.4 hrv-analysis

hrv-analysis¹⁰ is another free, open-source Python package designed for HRV analysis. It offers a comprehensive suite of methods for examining HRV in the time, frequency, and non-linear domains. The package also provides useful tools for preprocessing HR signals, such as identifying and removing outliers and ectopic beats.

The Authors validated their library by comparing it against Kubios HRV. The validation study found that time-domain features calculated by hrv-analysis and Kubios software were almost identical. Minor discrepancies are likely due to different mathematical approximations used by each program.

For frequency-domain features, some notable differences were observed between the two tools. These variations can be attributed to several factors. For example, hrv-analysis uses scipy for its calculations, while Kubios employs its own distinct implementation. Kubios also may use specific, unstated parameters for processes like window functions and detrending, which can influence results. Differences in data precision (for instance, float32 vs. float64) can lead to minor variations in calculations as well. Even the way the Fast Fourier Transform (FFT) is implemented can differ between software, contributing to varying outputs. Despite these differences in frequency-domain results, the authors concluded that all features remain medically relevant because their order of

¹⁰ <https://github.com/Aura-healthcare/hrv-analysis> (last accessed 08/15/2025)

magnitude is consistent across both analysis methods. Additionally, when normalized to $LFnu$ and $HFnu$ or presented as LF/HF ratio, the over and underestimations in the LF and HF features diminished, which tends to validate the accuracy of their functions. The library follows a two-step process, where the first step involves preprocessing the ECG signal by detecting and replacing outliers/ectopic beats using linear interpolation. The second step then covers basic feature calculation [CRL21].

Example.

```
1 from hrvanalysis import get_time_domain_features
2 from hrvanalysis import remove_outliers, remove_ectopic_beats, interpolate_nan_values
3
4 # Load ECG signal
5
6 # R-Peak detection
7
8 # Remove outliers and ectopic beats
9 rr_intervals_clean = hrvanalysis.remove_outliers(rr_intervals, low_rri=300, high_rri=2000)
10 rr_intervals_clean = hrvanalysis.remove_ectopic_beats(rr_intervals_clean, method="malik")
11 rr_intervals_clean = hrvanalysis.interpolate_nan_values(rr_intervals_clean)
12
13 # Calculate HRV
14 time_domain_features = get_time_domain_features(rr_intervals_clean)
15
16 # Print HRV
17 print(f"RMSSD: {time_domain_features['rmssd']:.2f} ms")
```

5.5 Evaluation of Existing Tools

There is an extensive amount of tools available for HRV analysis, each with its own benefits and drawbacks. To decide which tool to use at the end for this research, all tools presented above were tested on the same signal and compared against each other. Focus was put on the ease of use, preprocessing and R-Peak detection capabilities, as well as the accuracy of the HRV calculations when compared to each other.

In terms of preprocessing abilities, BioSPPy and NeuroKit2 both offer their own modules to handle various noise and artifacts. Both libraries did equally well when tested, although an own implementation could provide more flexibility and control over preprocessing steps, which could help when adjustments are needed to handle specific signals.

NeuroKit2 has a `ecg_peaks()` function that detects R-peaks extremely well with their default 'neurokit' algorithm. It locates QRS complexes by identifying steep changes in the absolute gradient of the ECG. R-peaks are then found as the highest points within these complexes¹¹. This method is unpublished, but validated here [Bra20]. When tested on the same signal, it detected and interpolated peaks in cases where R-peaks were suppressed or missing due to noise.

¹¹ <https://github.com/PIA-Group/BioSPPy/> (last accessed 08/15/2025)

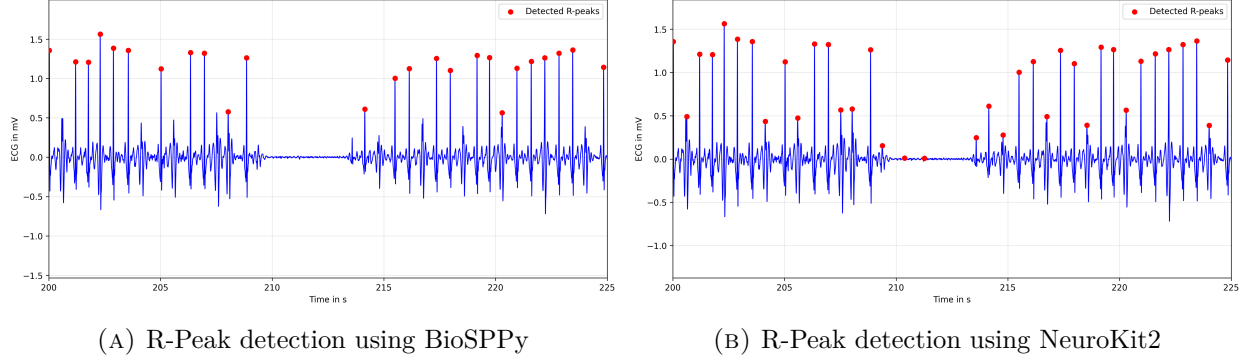


FIGURE 10: Preprocessing example

When comparing the HRV calculations, time-domain as well as nonlinear parameters were almost identical across all tools. However frequency-domain parameters differed mostly. This is likely due to the different implementation approaches for PSD calculation as mentioned before. Nevertheless, for analyzing trends, either tool would be sufficient according to the papers that validated them.

6 Concept

This section will present the concept of this thesis which is build upon the insights gained from all the findings above. The system architecture demonstrates the steps needed to be taken to extract and analyze HRV features from raw ECG data. The data, on which this specific experimental setup is based on, will be outlined. The main objective here is to eventually identify the proposed trauma signatures in unknown test data. It is to note however that many analysis steps taken are in consideration to the context of the data used in this thesis.

6.1 Data Exploration

The data for this thesis was provided by the *Clinic and Polyclinic for Psychiatry and Psychotherapy within the Center for Neurosciences at the University Medical Center of Rostock*. It comprises a set of medical time series acquired from individuals who were subjected to a simulated Eye Movement Desensitization and Reprocessing (EMDR) therapeutic intervention.

Info. An EMDR therapy session is a controlled environment where patients are exposed to upsetting mental images related to a traumatic event in a safe and monitored setting. Their emotional distress is then disrupted by a separate stimulus, known as bilateral stimulation (BLS). This interruption of attention is believed to reduce the patient’s emotional arousal and distress [Wri+24]. This approach has been proven effective in treating cases of over-arousal, including in patients with diagnosed PTSD [Bal+22; Sac+08]. This procedure allows for the collection of physiological data, such as ECG, while the patient is undergoing the therapeutic process. It has to be noted that this data collected from a simulated EMDR which differs from an actual EMDR therapy because it does not involve therapeutic interaction with a trained therapist.

For every participant, therapy was structured into 6 blocks, where each block consists of around 2-3 minute trauma exposure through individualized scripts for each participant. This approach is similar to [SCH12]. These scripts include personal negative experiences to induce emotional distress as well as positive and neutral imagery to generate emotional changes artificially. Every block starts off with negative scripts and ends with either negative, positive or neutral scripts. Each block has a reading and imagery phase, where the participant is asked to read the script and then imagine the described situation. These phases change relatively quickly in about 30-40 seconds or under. There are 3 blocks with BLS and 3 blocks without BLS, however the order of these is randomized. After 3 blocks, there is a 20 minute break for each participant, where the signal was paused and later continued. Figure 11 shows digital inputs throughout each therapy session, where each digital channel represents a different phase of the therapy.

Info.

- Digital_0 = Script 1 of the pair, Reading Phase (always negative)
- Digital_1 = Script 1 of the pair, Imagine Phase (always negative)
- Digital_2 = Script 2 of the pair, Reading Phase (negative, neutral or positive)
- Digital_3 = Script 2 of the pair, Imagine Phase (negative, neutral or positive)

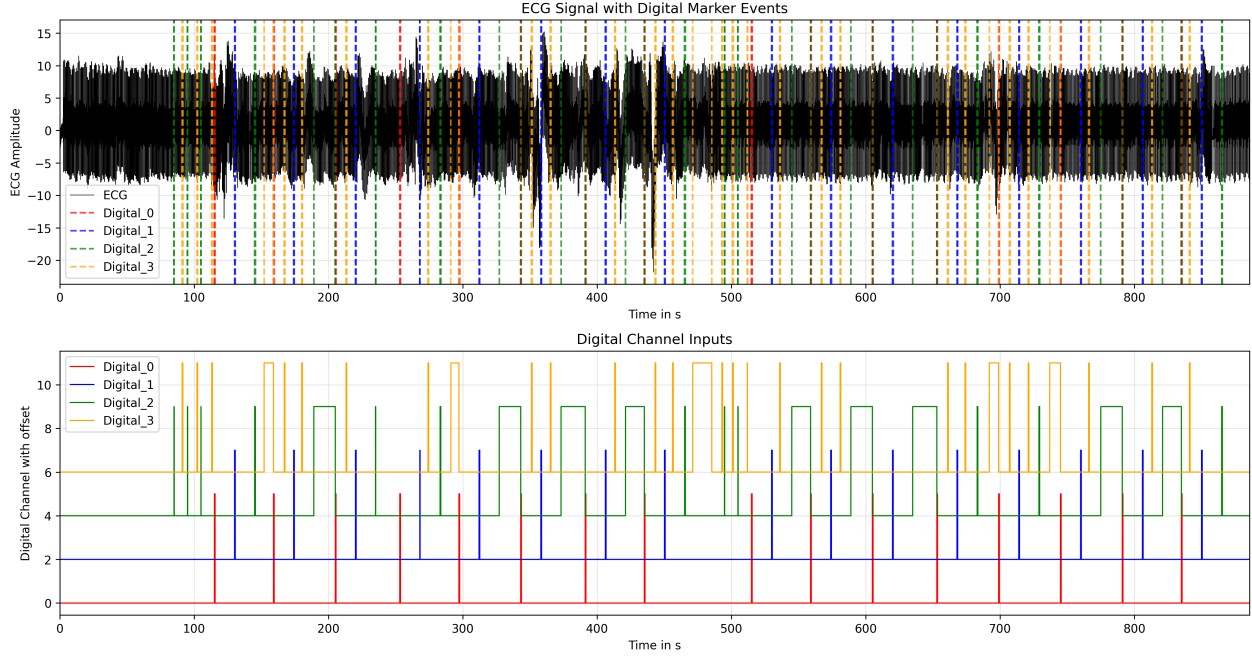


FIGURE 11: Digital inputs during therapy

The dataset consists of 60 recordings from where 31 are patients with diagnosed PTSD and 29 are healthy controls. Each recording is about 15 minutes long and contains among others (EDA, PPG, EMG, PPGED-R) an ECG signal sampled at a frequency of 2000 Hz. It is to note that for obvious reasons, some of the recordings can contain various types of noise and artifacts, such as through movement, BLS or other external influences. It is also possible that some individuals may have underlying conditions unknowingly that could potentially affect their overall HRV. This should be considered when data is processed and later interpreted.

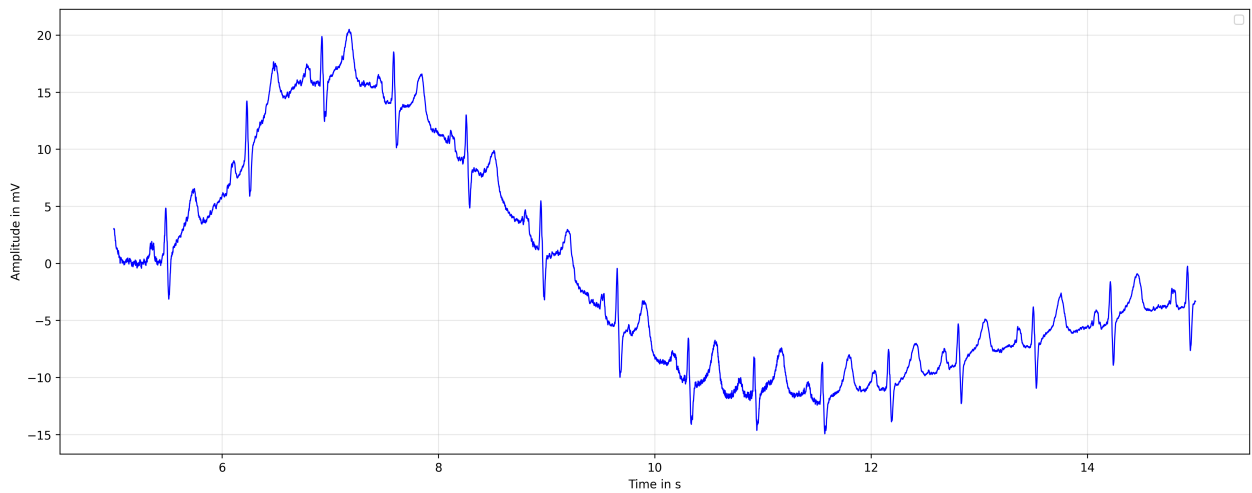


FIGURE 12: ECG signal with noticeable baseline wander and prominent T waves

6.2 Experiment Hypotheses

Info. Researchers who monitored multiple EMDR therapy sessions across PTSD patients, found that when BLS began, patients showed signs of calming - their HR dropped and HRV increased. This suggests an immediate de-arousal or relaxation response. As the stimulation continued while patients processed traumatic memories, stress indicators emerged - HRV decreased while breathing rate and HR increased. This indicates the expected stress response from confronting traumatic material. Despite moment-to-moment fluctuations, across entire sessions there was a progressive calming effect. Heart rate steadily decreased and HRV increased throughout treatment sessions, suggesting patients were becoming less physiologically activated over time. This provides objective evidence that EMDR produces measurable physiological changes consistent with reduced trauma-related arousal. The pattern suggests that while processing traumatic memories creates temporary stress responses, the overall effect is substantial calming and de-arousal - which aligns with EMDR's therapeutic goals of reducing trauma symptoms [Sac+08].

Based on all findings above, and assuming they hold to be true, following hypotheses are being proposed to guide the evaluation of this experiment:

- H1:** *At start and throughout the therapy session, individuals diagnosed with PTSD will exhibit significantly lower HRV compared to healthy controls. Especially, participants with PTSD will show reduced SDNN, RMSSD, pNN50, LF and HF power, as well as an elevated HR and LF/HF ratio.*
- H2:** *A shift in emotional valence from baseline to negative will cause individuals diagnosed with PTSD to exhibit significant reduction in HRV compared to healthy controls.*
- H3:** *By the end of the therapy session, patients with PTSD will demonstrate an increase in HRV, reflecting the potential calming and regulatory effects of the EMDR intervention.*
- H4:** *By the end of the session, the control group will show an increase in HRV, indicating a mild calming effect of the therapy process.*

6.3 System Architecture

The system architecture is divided into multiple components. First, the data is being processed to remove noise and artifacts for the purpose of extracting proper R-peaks. Once the R-peaks are detected, the RR intervals are extracted and desired HRV features derived. Lastly, the HRV calculations will be visualized and analyzed statistically to compare results between PTSD patients and the control group. For statistical analysis, a *Mann-Whitney-U test* will be performed to evaluate significant differences between the groups while *Cohen's d* will be used to measure the effect sizes of HRV indices. Additionally, a *Wilcoxon Signed-Rank test* will be utilized to assess within-group changes between HRV at two different time points.

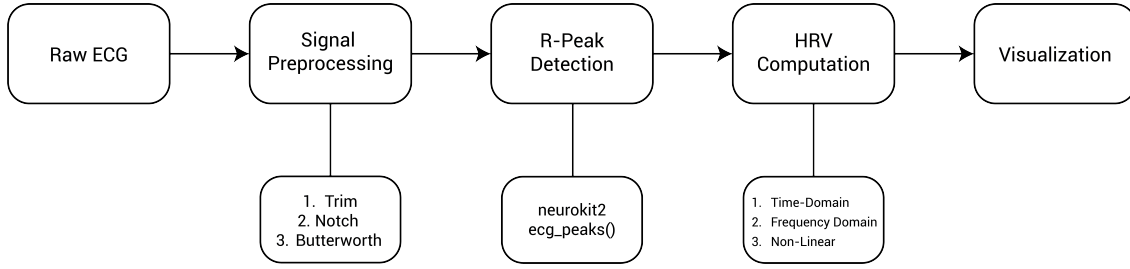


FIGURE 13: HRV analysis pipeline

6.3.1 Data Preprocessing

For every participant, the ECG signal was extracted from the raw .CSV file. Every Signal was visualized and vastly inspected. Those with excessive noise, artifacts or for example missing recording segments were excluded from the analysis entirely. From the 15-minute ECG recorded for every participant, a middle ECG segment was separated to remove artefacts at start-up and at the end of the recording.

To preprocess the data, each ECG signal had a 50Hz notch filter applied. For Bandpass filtering, a separate butterworth filter was implemented with a cutoff frequency of 5-35 Hz and an order of 4. NeuroKit2 was then used to detect R-peaks in the signal.

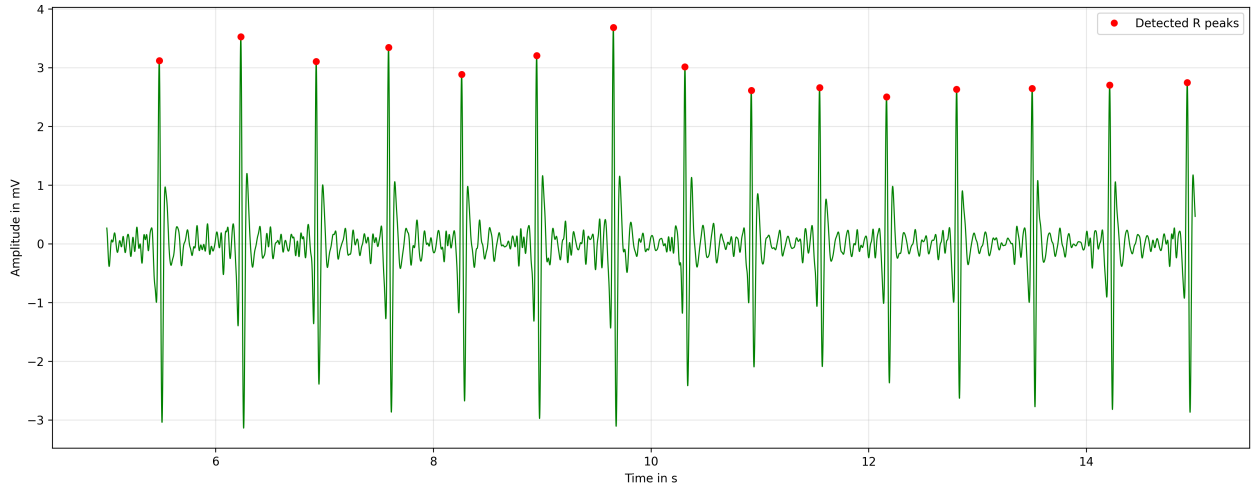


FIGURE 14: ECG signal after filtering and R-peak detection

6.3.2 HRV Extraction

After determining the RR intervals, pyHRV was used to calculate the desired HRV features on the entire signal for each participant, constituting an ST analysis of around 13-15 minutes. Moreover, to be able to analyze temporal trends within the ECG itself, the RR intervals were windowed into multiple consecutive ST (5 min) and UST(2 & 3 min) segments before HRV was calculated for each window.

Info. There are challenges and considerations of using UST durations in HRV analysis for stress

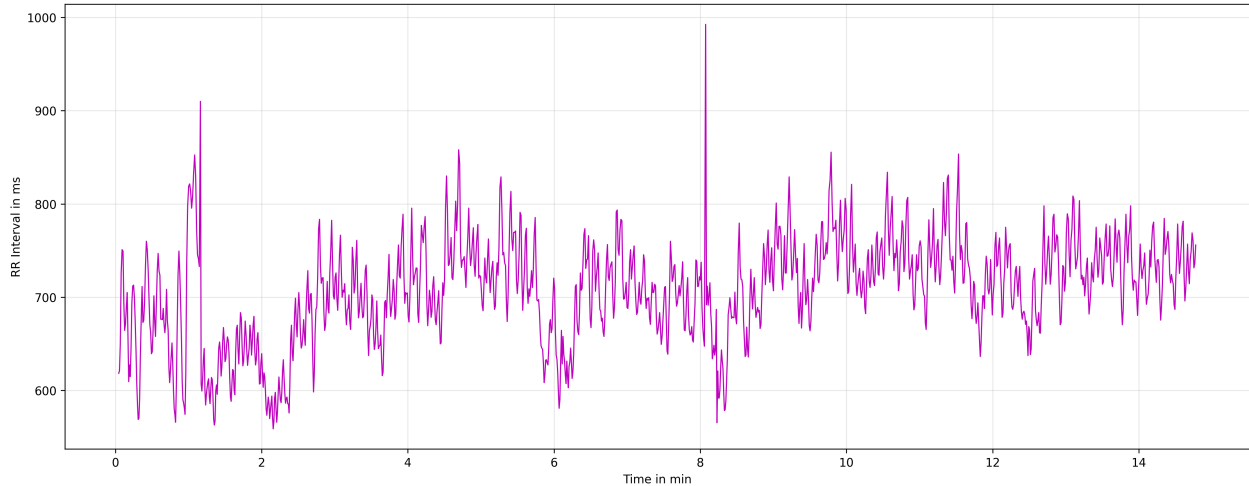


FIGURE 15: Example of a RR interval time series from the dataset

detection and health monitoring. The choice of signal length and window size can significantly impact the results. While shorter time windows can enable real-time monitoring, they may also filter out valuable information. Time-domain metrics can be more robust to signal shortening. On the contrary, frequency-domain and non-linear metrics can be more accurate, but also sensitive to signal reductions, where shorter windows may often lead to increased values. In most cases, a 5-minute window is considered for stress analysis and UST periods (1-3 minutes) for real-time analysis. [IKK21; Ury+25].

While 5-minute HRV recordings remain the gold standard for stress analysis, some studies suggest that UST durations of 1-4 minutes can still be effective in resting conditions [Jin+24]. [Bur+21] investigated this, whether very short HRV recordings can reliably replace the standard 5-minute recordings typically used in clinical and research settings. They found that the accuracy and reliability of HRV measurements improved with longer recording durations: *HR* was accurate with recordings of ≥ 1 minute. Time-domain HRV metrics were still reliable with recordings of ≥ 4 minutes. However, frequency-domain HRV metrics required the full 5 minutes. Importantly, shorter recordings were more susceptible to interference from breathing patterns, blood pressure changes, and other physiological factors that could skew results. On the other hand, [Tom+25] found mixed results with only *VLF*, *HF*, *SD1* and *SDtwo* showing good reliability with 30 second recordings or also *SDNN* and *RMSSD* being sufficient with 1 minute recordings [SSM16].

Since every block of the experiment starts off with a negative phase, HRV was also calculated for the first (~ 30) seconds of baseline as well as for the subsequent first negative valence phase (reading and imagining) of around 30 seconds. The change score between these two phases (Δ Neg-Base) was then calculated for each HRV metric.

For each participant, calculations return a single row dataframe, which are then bound into one single dataframe similarly to [Pha+21]. The next section showcases some of the visualizations created throughout the evaluation-process.

6.3.3 Data Visualization

To visualize the results, mainly boxplots such as Figure 17 were created to compare HRV metrics between the two groups. Figure 18 shows an example of how effect sizes were visualized inspected throughout evaluation. For *future research purposes*, additional plots (Figure 21, 20, 19) were generated in regards to different script inputs. Moreover, an option for defining *sliding windows* was implemented additionally into the HRV analysis pipeline (in source code 1). This allows to generate a continuous HRV plot and shall help for a deeper analysis of quick to instantaneous HRV responses through form of real-time monitoring, helping to potentially identify changes in emotional valence during therapy with a dynamic view of HRV. The usage of it however, will not be further evaluated in this thesis.

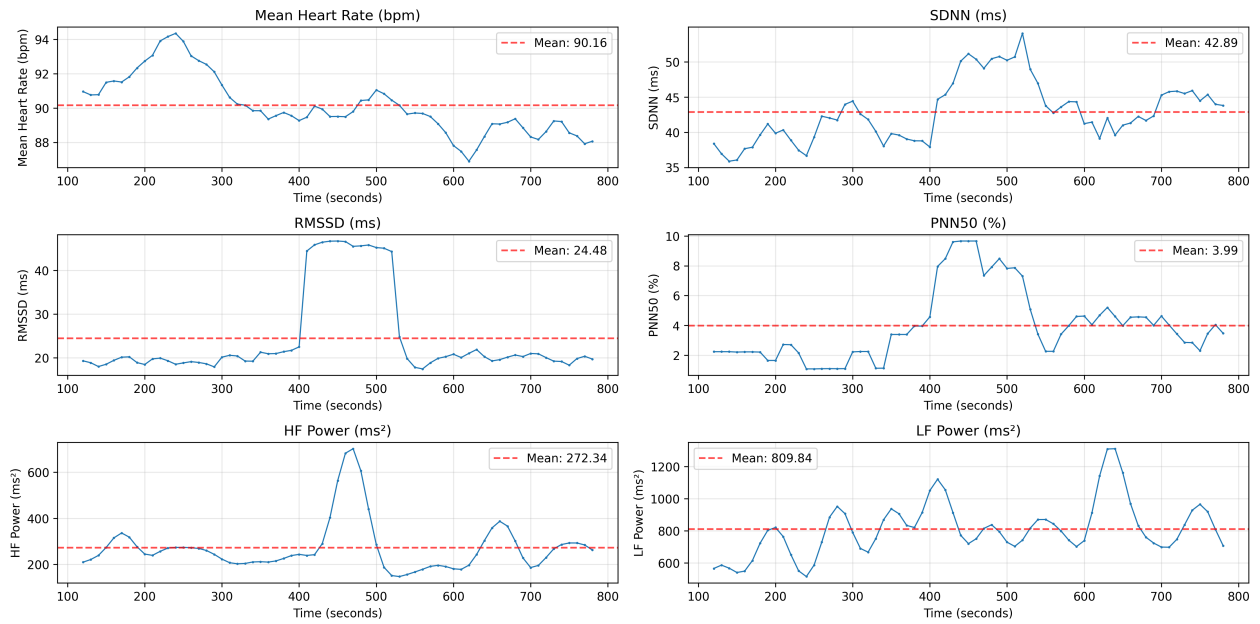


FIGURE 16: HRV progression across time, calculated on sliding windows (window size=120s, overlap=110s)

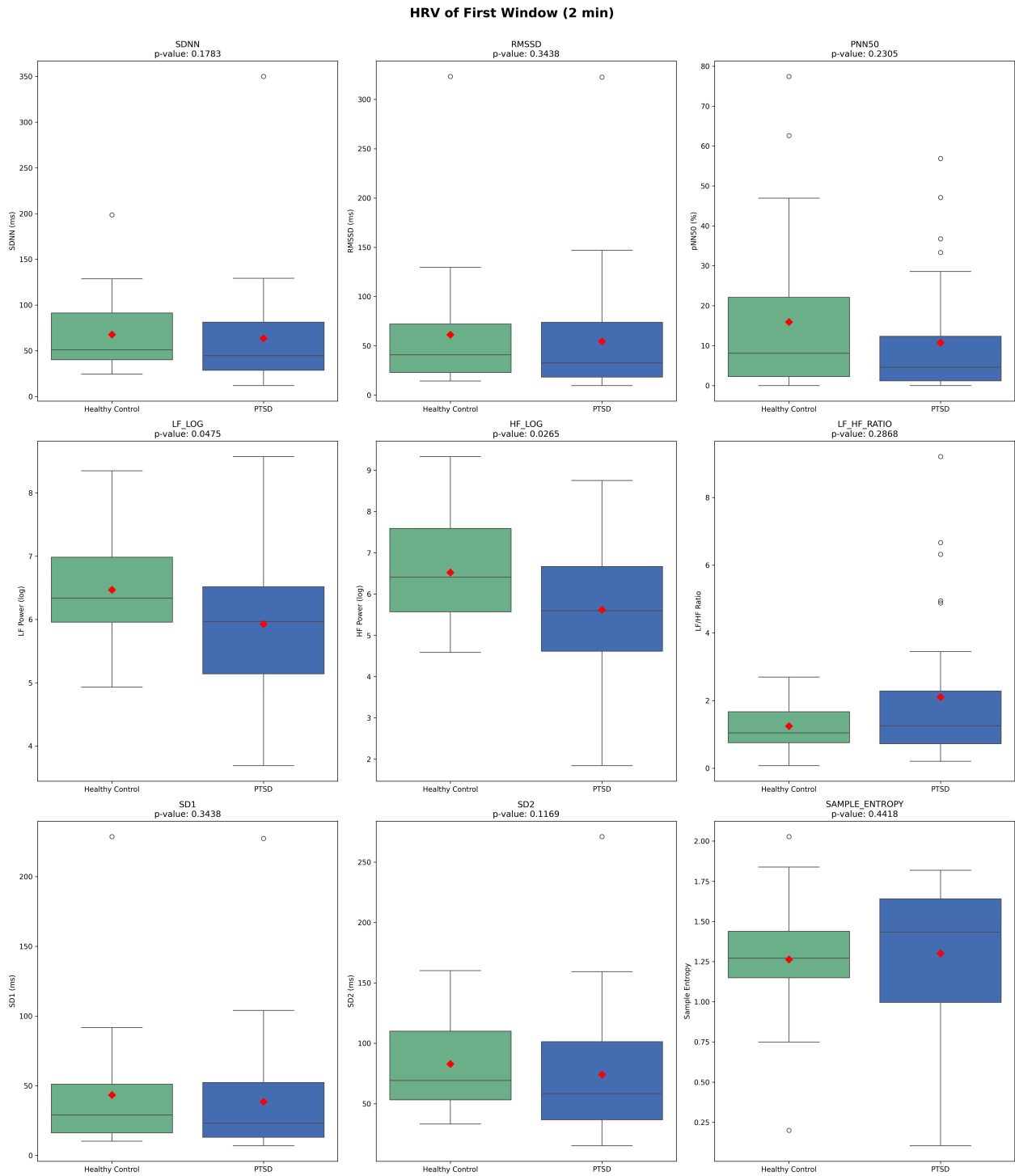


FIGURE 17: HRV comparison of 1st window (2 min) between groups

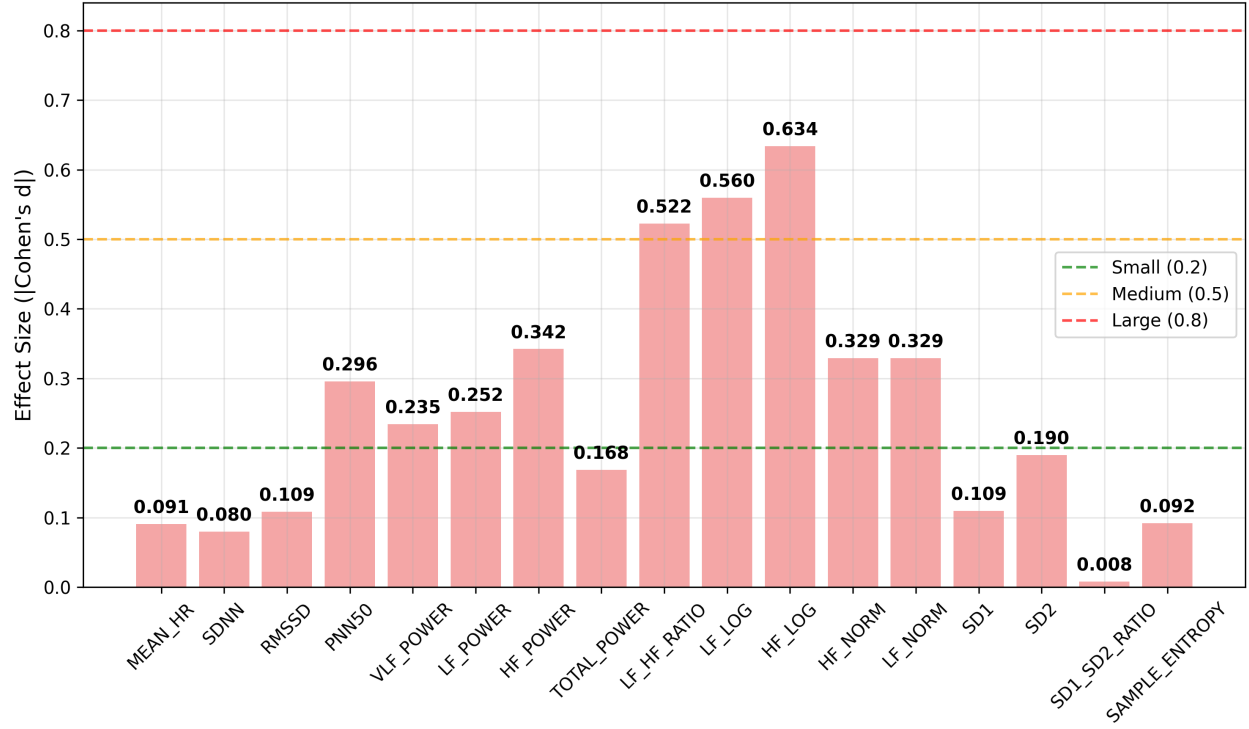


FIGURE 18: Cohen's d effect sizes between healthy Controls and PTSD patients of 1st window (2 min)

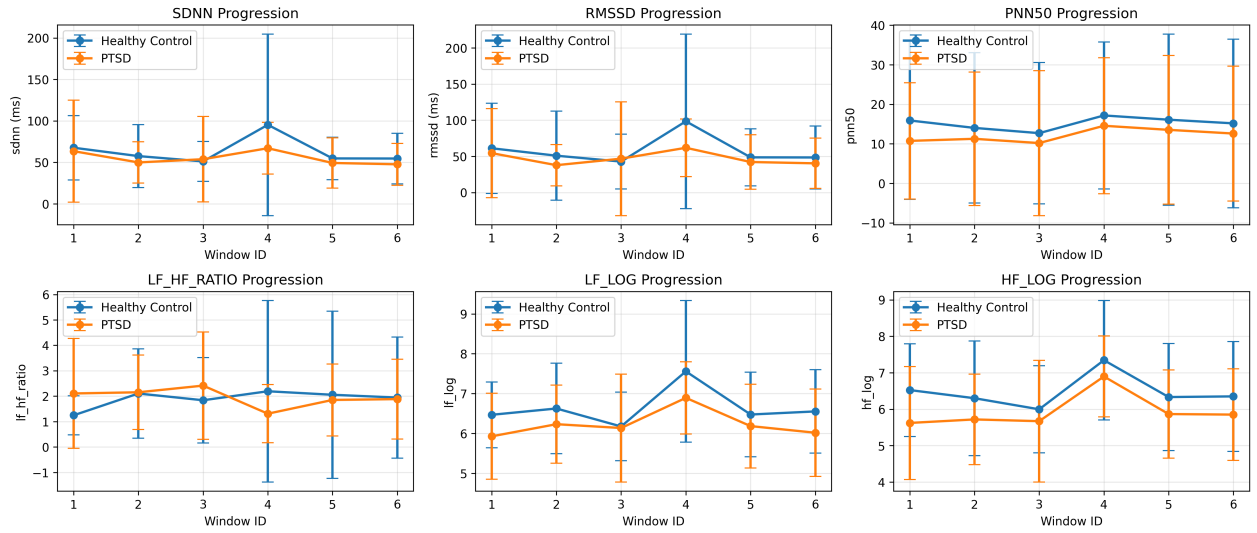


FIGURE 19: HRV progression across time windows (2 min) for groups

6. Concept

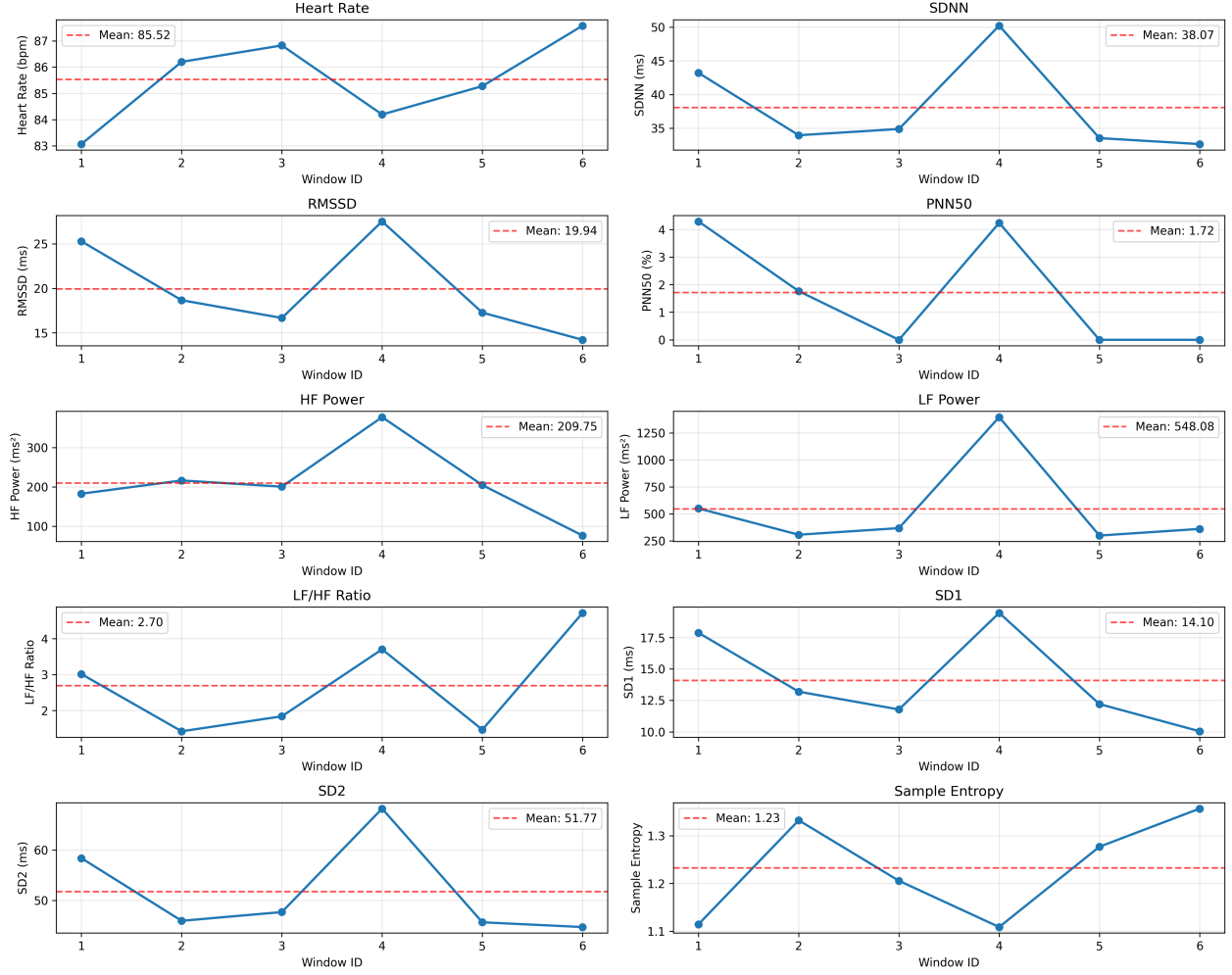


FIGURE 20: HRV progression throughout windows (2 min) for single patient

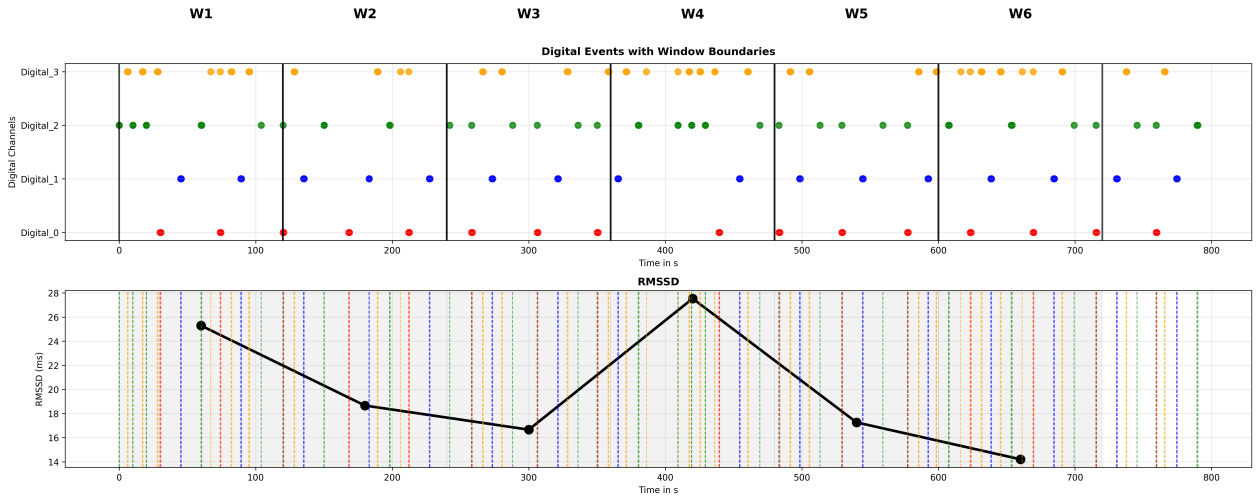


FIGURE 21: Detailed HRV progression throughout windows (2 min) for single patient Valence change analysis

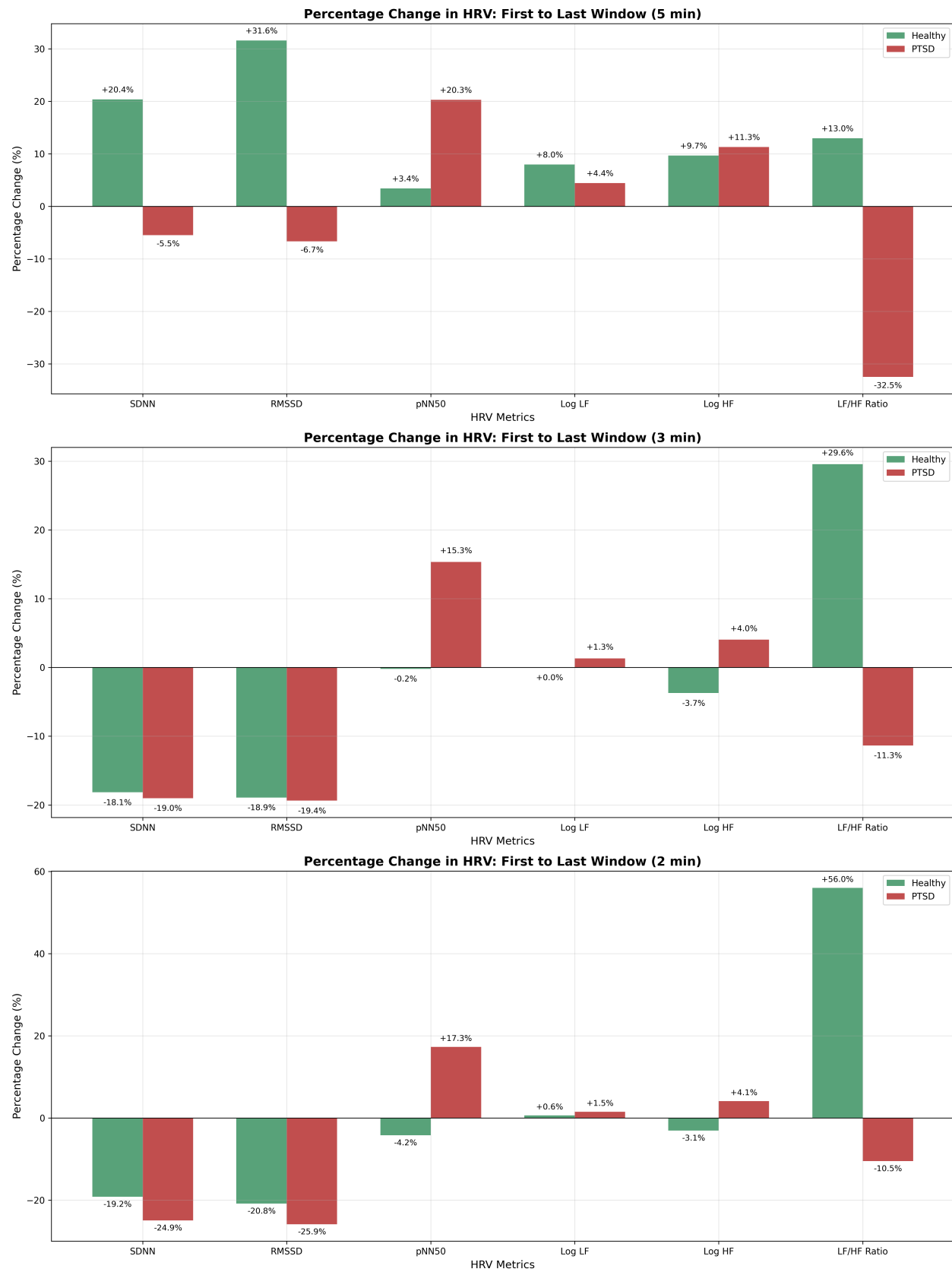


FIGURE 22: HRV window comparison between first and last window

7 Results

This section presents the results of the HRV analysis conducted on the EMDR therapy data. The results are organized into several subsections, each focusing on different aspects of the analysis.

Entire Signal Analysis

Analysis of HRV variables calculated on the entire signal (~ 15 min) for each participant is presented in Table 7. Significant differences are shown for *HF* ($p = 0.0332$), while *LF* power is approaching significance ($p = 0.0545$). Small effect sizes (Cohen's $d > 0.2$) were observed for *RMSSD*, *VLF*, *TP*, *LF*, *HF*, *LF/HF*, *SD1* and *SD1/SD2 ratio*.

First Window Analysis

Results of the first window analysis (5 min) are shown in Table 8. No significant differences were found between the groups. Small effect sizes could be observed for *SDNN*, *RMSSD*, *VLF*, *LF*, *LogHF*, *TP*, *SD1* and *SD2*.

Results of the first window analysis (3 min) are shown in Table 3. Significant differences were found in *HF* power ($p = 0.0412$). A Trend towards significance was noted in *LF* power ($p = 0.0509$). Small effect sizes could be observed for *pNN50*, *TP* and *SD2* whereas medium effect sizes (Cohen's $d > 0.5$) were observed for *LF*, *HF* power.

Results of the first window analysis (2 min) are shown in Table 4. Significant differences were found in *HF* power ($p = 0.0265$) and *LF* power ($p = 0.0475$). A trend towards significance was found in *TP* ($p = 0.0711$). Small effect sizes were observed for *pNN50*, *VLF* and *TP* whereas medium effect sizes were observed in *LF* and *HF* power as well as *LF/HF*.

Last Window Analysis

Results for the last windows (5 min, 3 min & 2 min) are shown in Table 10, 11 and 12. No significant differences were found between the groups. Though there was a trend towards significance shown in *LF* ($p = 0.0784$) for the last 5 min window.

First and Last Window Comparison

HRV changes between the first and last windows are visualized in Figure 22. A significant increase in *LogHF* ($p = 0.0458$) was found in the PTSD group when comparing the change score from the first to last 3 minute window, compared to healthy controls.

Within-group changes, showed significant changes between the first and last 2 minute windows. For healthy controls, there was a significant decrease in *HR* ($p=0.0092$) and *SD2* ($p=0.0386$). For PTSD patients, there was a significant decrease in *HR* ($p=0.0029$), *SDNN* ($p=0.0209$) and *SD2* ($p=0.0233$).

Within-group changes, showed significant changes between the first and last 3 minute windows. For healthy controls, there was a significant decrease in *HR* ($p=0.0041$), *VLF* ($p=0.0431$) and *SD2* ($p=0.0229$) as well as a increase in *LF/HF ratio* ($p = 0.0455$). For PTSD patients, there was a significant decrease in *HR* ($p=0.0009$) and *SD2* ($p=0.0321$) as well as an increase in *LF/HF ratio* ($p = 0.0140$).

Within-group changes, showed significant changes between the first and last 5 minute windows. For healthy controls, there was a significant decrease in *HR* ($p=0.0106$) and *SD1/SD2 ratio* ($p=0.0065$) as well as a increase in *VLF* ($p=0.0179$), *LogLF* ($p=0.0179$) *LogHF* ($p=0.0005$) and *TP* ($p=0.0001$). For PTSD patients, there was a significant decrease in *HR* ($p=0.0041$) and *LF/HF ratio* ($p=0.0081$) as well as increase in *pNN50* ($p=0.0414$), *LogLF* ($p=0.0374$), *LogHF* ($p=0.0002$) and *TP* ($p=0.0097$).

Windowed Analysis of Entire Signal

Table 13 shows the results for the entire signal with windows of 5 minutes. Significant difference was found in *LF* ($p = 0.0491$). *LogLF* was however slightly off significance ($p = 0.0512$). A trend towards significance was noted in *LogHF* ($p = 0.0623$). Small effect sizes were observed in *SDNN*, *RMSSD*, *VLF*, *SD1* and *SD2*. Medium effect was shown in *HF* and *LogLF*.

Table 14 shows the results for the 3 minute window analysis of the entire signal. No significant differences were found between the groups. Trends towards significance could be seen in *LogLF* ($p = 0.0666$) and *LogHF* ($p = 0.0976$). Small effect sizes were observed in *SDNN*, *RMSSD*, *VLF*, *LogLF*, *LogHF*, *SD1* and *SD2*.

Table 5 shows the results for the 2 minute window analysis of the entire signal. Significant main effects were observed for *LF* ($p = 0.0159$) *HF* ($p = 0.0159$), *TP* ($p = 0.0427$). It is to note that *LogLF* is slightly off significance ($p = 0.0666$). Effect sizes were small for *SDNN*, *RMSSD*, *VLF*, *LF*, *HF*, *SD1* and *SD2*.

HRV Valence Change Analysis

Table 6 shows the results for the HRV changes from baseline to negative valence (Δ Neg-Base). Significant decreases were found in *pNN50* ($p = 0.0215$) and *LogHF* ($p = 0.0236$) for the PTSD group compared to healthy controls.

Within-group changes, showed significant changes between baseline and the first negative valence phase. For healthy controls, there was a significant decrease in *SDNN* ($p=0.0386$) and *LogLF* ($p=0.0365$). For PTSD patients, there was a significant decrease in *SDNN* ($p=0.0017$), *RMSSD* ($p=0.0020$), *pNN50* ($p=0.0012$), *LogLF* ($p=0.0198$), *LogHF* ($p=0.0005$), *TP* ($p=0.0149$), *SD1* ($p=0.0020$) and *SD2* ($p=0.0054$).

HRV metric	Healthy Control (n=29)	PTSD (n=31)	p-Value
Mean HR	81.02 $\pm$ 11.29	81.89 $\pm$ 7.73	0.6150
SDNN	67.67 $\pm$ 38.85	63.53 $\pm$ 61.50	0.1783
RMSSD	61.24 $\pm$ 62.28	54.52 $\pm$ 61.44	0.3438
pNN50	15.91 $\pm$ 19.99	10.75 $\pm$ 14.74	0.2305
VLF	1167.24 $\pm$ 728.33	1510.58 $\pm$ 1910.15	0.3828
LF	913.84 $\pm$ 909.30	675.26 $\pm$ 981.91	0.0475*
HF	1512.43 $\pm$ 2315.00	840.60 $\pm$ 1564.78	0.0265*
TP	3593.51 $\pm$ 3070.51	3026.43 $\pm$ 3624.34	0.0711
LF/HF Ratio	1.25 $\pm$ 0.77	2.10 $\pm$ 2.16	0.2868
Log LF	6.47 $\pm$ 0.83	5.93 $\pm$ 1.08	0.0475*
Log HF	6.52 $\pm$ 1.27	5.62 $\pm$ 1.55	0.0265*
HFnu	50.11 $\pm$ 18.22	43.75 $\pm$ 20.25	0.2868
LFnu	49.89 $\pm$ 18.22	56.25 $\pm$ 20.25	0.2868
SD1	43.30 $\pm$ 44.04	38.52 $\pm$ 43.32	0.3438
SD2	82.93 $\pm$ 37.69	74.20 $\pm$ 52.46	0.1169
SD1/SD2 Ratio	2.61 $\pm$ 1.00	2.60 $\pm$ 1.29	0.6046
SampEn	1.26 $\pm$ 0.36	1.30 $\pm$ 0.43	0.4418

TABLE 4: HRV results 1st window (2 min) presented as: Mean $\pm$ (Std).*Statistically significant ($p < 0.05$).

HRV metric	Healthy Control (n=29)	PTSD (n=31)	p-Value
Mean HR	79.54 $\pm$ 10.64	80.26 $\pm$ 7.90	0.8824
SDNN	63.40 $\pm$ 32.06	55.23 $\pm$ 29.15	0.1599
RMSSD	58.33 $\pm$ 46.31	47.30 $\pm$ 36.57	0.1783
pNN50	15.18 $\pm$ 19.30	12.16 $\pm$ 16.60	0.7561
VLF	22401.92 $\pm$ 114340.56	1728.43 $\pm$ 3621.34	0.3289
LF	18791.63 $\pm$ 93179.27	1641.92 $\pm$ 4843.97	0.0159*
HF	3027.37 $\pm$ 5616.02	1932.01 $\pm$ 6028.79	0.0159*
TP	44220.92 $\pm$ 212152.07	5302.36 $\pm$ 14378.39	0.0427*
LF/HF Ratio	1.89 $\pm$ 1.38	1.95 $\pm$ 1.10	0.5740
Log LF	6.63 $\pm$ 0.74	6.23 $\pm$ 0.90	0.0666
Log HF	6.47 $\pm$ 1.15	5.94 $\pm$ 1.16	0.0442*
HFnu	46.26 $\pm$ 15.70	43.37 $\pm$ 14.43	0.4962
LFnu	53.74 $\pm$ 15.70	56.63 $\pm$ 14.43	0.4962
SD1	41.24 $\pm$ 32.75	33.44 $\pm$ 25.86	0.1783
SD2	77.53 $\pm$ 34.13	68.00 $\pm$ 31.97	0.1880
SD1/SD2 Ratio	2.59 $\pm$ 0.80	2.66 $\pm$ 0.78	0.7900
SampEn	1.32 $\pm$ 0.30	1.32 $\pm$ 0.28	0.7787

TABLE 5: HRV results full windowed analysis (2 min) presented as: Mean $\pm$ (Std).*Statistically significant ($p < 0.05$).

HRV metric	Healthy Control (n=29)	PTSD (n=31)	p-Value
Mean HR	-1.24 ± 5.24	$+2.14 \pm 6.62$	0.1135
SDNN	-11.27 ± 45.40	-39.30 ± 131.34	0.2802
RMSSD	-11.43 ± 57.97	-51.05 ± 134.13	0.1981
pNN50	-0.17 ± 9.66	-6.69 ± 13.60	0.0215*
VLF	-452.60 ± 1563.26	-132.64 ± 2239.84	0.1599
LF	-992.88 ± 2416.31	-364.80 ± 1492.72	0.9764
HF	-454.45 ± 2360.57	-900.73 ± 2617.15	0.0809
TP	-1899.93 ± 5334.58	-1398.18 ± 4719.55	0.4330
LF/HF Ratio	$+0.20 \pm 4.40$	$+0.53 \pm 3.95$	0.3828
Log LF	-0.56 ± 1.44	-0.55 ± 1.40	0.6465
Log HF	-0.29 ± 1.28	-0.90 ± 1.35	0.0236*
SD1	-8.06 ± 41.06	-35.80 ± 93.33	0.1930
SD2	-13.63 ± 51.96	-30.63 ± 98.44	0.5151
SD1/SD2 Ratio	$+0.29 \pm 1.69$	$+0.70 \pm 1.86$	0.2547

TABLE 6: HRV changes from baseline to negative valence (Δ Neg-Base) between group comparison presented as: Mean $\pm$ (Std).

*Statistically significant ($p < 0.05$).

8 Discussion

This section will discuss the results and findings of this thesis. First by evaluating the hypotheses presented in 6.2, determining whether the evidence supports or refutes them. Finally, potential limitations of both the results and the overall thesis will be outlined.

8.1 Hypothesis-driven Evaluation of Results

H1 *proposes a reduction in HRV for PTSD patients compared to healthy controls at the start and during therapy.* While not definitively proven nor disproven, the results support this hypothesis partially, as the PTSD group mostly showed lower values in *LF* and *HF* power compared to the healthy control group. 1st window analysis of 3 & 2 minutes segments show that patients with PTSD already start off with reduced *LF* and *HF*. Additionally, when HRV is calculated for the entire recording (Table 7, Figure 23), significant differences were also found in the *LF* and *HF* power bands. This suggests that PTSD causes long term effects of parasympathetic withdrawal and general PNS dysfunction. Even when not always fully substantial, some results still show trends towards significance for *LF* and *HF*, which suggests that the data is leaning into a particular direction. This implies that with a larger sample size or more data, the results might become statistically significant. *HF* being a strong indicator also aligns with findings of most other studies presented in 3. Expecially in this particular study [Moo+13], where explicitly the PTSD group only revealed significantly lower values in *HF*.

Throughout all analyses, even if not statistically significant, the PTSD group generally and visually (as seen in 6.3.3) showed lower means in HRV (*SDNN*, *RMSSD*, *pNN50*, *VLF*, *LF*, *HF*, *TP*, *SD1* and *SD2*), with those metrics having commonly small effect sizes. This trend was consistent throughout all analyses, indicating a subtle and potentially important difference between these two groups. This small level of effect could have meaningful implications, especially when considering how HRV changes can differ from person to person. For example, smaller effects might be observed when comparing the HRV of individuals with different levels of fitness.

H2 *suggests that a shift in emotional valence from baseline to negative will cause individuals diagnosed with PTSD to exhibit a significant reduction in HRV.* The hypothesis is strongly supported by a significant decrease in *pNN50* and *LogHF* in the PTSD group compared to healthy controls. This indicates that the PTSD group, compared to controls, had a more pronounced reduction in these HRV metrics when exposed to negative stimuli, suggesting a *heightened stress reaction* and *reduced parasympathetic activity*. This finding aligns with the understanding that PTSD is associated with autonomic dysregulation and a reduced ability to adaptively respond to stressors. This expecially, is supported when comparing changes in HRV before and after baseline within group measurements. From baseline to negative valence, the healthy control group showed significant reductions in *SDNN* and *LogLF*, whereas the PTSD group exhibited significant reductions in multiple parameters (*SDNN*, *RMSSD*, *pNN50*, *LogLF*, *LogHF*, *TP*, *SD1* and *SD2*). These results align heavily with findings from other studies presented in 3.

H3 and **H4** propose a slight increase in HRV for both groups by the end of the therapy session. When comparing change scores between the first and last 3 minute windows (Figure 22), the PTSD group showed a more pronounced increase in LogHF compared to the control group. This suggests that the PTSD group experienced a more pronounced *increase in parasympathetic activity*, due to the calming and regulatory effects of the EMDR intervention. This finding aligns with the understanding that effective therapeutic interventions such as BLS can help restore autonomic balance in individuals with PTSD. Another reason for the significant increase compared to the control group could be that the PTSD group already started off with significantly lower HF values, therefore had more room for improvement.

Results of within group measurements give evidence to support **H3** as well as **H4**. Both groups consistently showed significant decreases in HR . In addition, when comparing first and last 5 minute windows, both groups showed significant increases in frequency-domain parameters. The PTSD group also showed a prominent increase in $p\text{NN50}$. This indicates that both groups experienced a calming effect by the end of the therapy session, seen through increased HRV and thereby enhanced parasympathetic activity. However, it can be complicated to draw a definitive conclusion. While the 5 minute comparison showed promising results, in some cases, especially in shorter window sizes, some significant decreases in HRV were still observed, which is contrary to the hypothesis. Though, in this case, one can argue that 5 minute segments are considered to be the standard for stress evaluation and therefore hold more weight than the comparisons between shorter window sizes. Still, important metrics such as RMSSD did not show much or consistent significance throughout the analyses, making it sometimes inconclusive whether there was a general increase or decrease in HRV. Therefore the evidence may not be necessarily strong enough to conclude that the hypotheses **H3** and **H4** are true or false.

Overall, these findings suggest that while there are noticable differences in HRV (especially in LF & HF) between patients with PTSD and without, there is still a need for further research to understand on why not all metrics correspond with one another equally and why not all results are as expected based on what has been found in literature.

Results of smaller windows of under 5 minutes did not diverge heavily from the 5 minute analysis. Though as window sizes got smaller, results became more pronounced revealing *lower p-values* and therefore stronger evidence for LF and HF , indicating UST analysis to be effective for detecting changes in HRV. Moreover, significant differences were found in e.g. $p\text{NN50}$ and LogHF for UST durations of around 30 seconds when comparing changes from baseline to negative valence. This supports the idea of using UST analysis and perhaps a *sliding window* approach for real-time applications, such as for monitoring HRV during therapy, where short changes in emotion could be detected and possibly tracked. This could substantially improve the use and effectiveness of therapeutic interventions.

PTSD can manifest within the body, affecting the ANS and, consequently, a person's overall health. This can be observed when comparing the HRV values of individuals with and without

PTSD. The difference was particularly evident when HRV was measured at the beginning and throughout therapy.

In Section 3.2 it was mentioned that with HRV alone one cannot yet diagnose and distinct between specific mental illnesses or diseases. Therefore it should be viewed as a general indicator of autonomic health rather than a pure diagnostic tool for PTSD. Results must be interpreted alongside a patient's psychological and medical history or also in conjunction with other diagnostics - a *multimodal* approach.

8.2 Limitations

The results should be interpreted with caution. Possible complications to these findings could have arisen due to limitations of this study. Statistical significance was mostly found in log values, which suggests that the original *LF* and *HF* data may have contained outliers that could have skewed the results by introducing variability and bias. It is also highly possible that the sample size was simply not large enough for this study. Furthermore, window sizes of under 5 minutes are sometimes considered to be not ideal for frequency-domain analysis according to literature. Shorter window segments can lead to less reliable estimates of frequency-domain parameters. In some cases even, *SampEn* had to be excluded from analysis, since the short length of the segments led to unusable results.

Even though every signal was briefly inspected, small sections with heavy and unrecoverable artifacts may still have been present, which could have affected the overall results. What could have been done differently whilst performing the analysis would have been manual RR interval inspection and maybe even manual correction, to ensure that no artifacts were present.

When literature was reviewed, some sources were used that were published a while ago, which could seem outdated. These sources were chosen because they still align with the current state of research, therefore these findings still hold value, but may rise concerns.

A major limitation is the simulated character of the session, making it not easily comparable to a real session with a genuine therapist. Consequently, the results cannot be readily transferred to a real-world setting. Differences from a real session primarily include the lack of interactivity during the session (association pathways were fixed and pre-defined, not generated by the participants themselves), the absence of a therapist, and the lack of choice regarding the type of stimulation for the patient (tactile BLS was pre-defined in speed and intensity - in a real session, the patient can choose between different types of stimulation and determine the speed themselves).

The exploration of stress response within therapy data is conflicting in some ways. This research aims to find correlations of HRV with trauma signatures by analyzing stress response, yet the ultimate goal of EMDR is the reduction of these very trauma symptoms. This approach contrasts with most other studies that focus exclusively on stress induction rather than stress relief. The research on HRV as a response to stress relief was less inspected in this thesis.

It should be noted that, in contrast to trauma-focused Cognitive Behavioral Therapy (tf-CBT), EMDR therapy is characterized by very short phases of stress induction or trauma confrontation. In tf-CBT, this confrontation is much more intensive, as the session essentially consists of the induction

of trauma-associated stress, and the therapeutic effect is explained by habituation after repeated exposure. Despite the very brief exposure phases in our simulated EMDR, we were still able to demonstrate a significant reduction in HRV, a finding that should be emphasized.

The simulated EMDR also involved artificially induced changes in valence, these changes happened within a matter of under 40s. The use and effectiveness of UST durations of such short time frames have been lightly investigated in this thesis but not fully evaluated.

A ST analysis duration of 5 minutes showed less effect than UST time frames in group comparisons, likely because the 13-15 minute signal was too short to provide an adequate amount of data. On top of that, a 5-minute duration for the ST analysis may have been long enough to allow for multiple positive shifts in emotional state (valence) and BLS, which may have interfered with the data and lessened the observed effect. This could also be the reason why most significant findings for and increase in HRV were found when comparing changes between first and last windows of 5 minutes. Therefore, a stronger focus on UST analyses of even under 1 minute could have been more beneficial for this particular experiment.

The results regarding the increase in HRV due to the simulated EMDR session must also be interpreted with caution, because there was a lack of control conditions such as a tf-CBT session or a Non-Intervention Control condition (no between-group design)! The increase could also be solely due to habituation.

Furthermore, the experiment as it was planned, included a 20 minute break within the measurements, which could have significantly distorted the results, since participants had the chance to relax and recover. This especially can be seen in most progression plots (seen in 20), where a noticeable spike in HRV can be observed within the time frame of the pause.

Due to time constraints, the analysis of the experiment was limited to only general group comparisons and two emotional states (baseline and negative valence) Furthermore BLS was not taken into consideration.

Generally people respond differently to psychological stressors. Some show mainly sympathetic activation, others show vagal (parasympathetic) withdrawal and some show a reciprocal pattern where both systems are responding [Pha+21]. Likewise to HR, the baseline HRV is highly individual and can be influenced by various factors such as age, sex, genetics, weight and fitness level. What also constitutes for “high” or “low” HRV varies considerably between people. This suggests HRV would be most useful when tracked over time within individuals rather than compared across different people [Han+25]. This thesis did not account for these variables.

9 Conclusion

This Bachelor's thesis explored medical time series data, specifically ECG to identify signatures that are indicative of psychological trauma. Particularly HRV was investigated as a biomarker. In the statement of purpose, research questions were posed, investigated and answered throughout this work.

Q1: *How does HRV reflect the psychological state?*

Contemporary research has shown there is a strong bidirectional relationship between mental health and cardiovascular function. Particularly, HRV is a well-established biomarker for the ANS health. It reflects the balance between the sympathetic and parasympathetic nervous systems, which are responsible for the body's stress response and recovery. Changes in HRV can indicate shifts in emotional states, stress levels, and overall autonomic function. Usually, higher HRV is associated with a more adaptive and resilient ANS whereas lower HRV indicates dysregulated ANS function and therefore a stressed and unhealthy mental state.

Q2: *How can HRV be derived from ECG data?*

HRV can be derived from ECG data by analyzing the time intervals between successive heartbeats, known as RR intervals. This involves preprocessing the ECG signal to remove noise and artifacts, followed by proper R-peak detection. Before then various time-domain, frequency-domain and non-linear HRV parameters can be computed. These metrics quantify the variability in HR and provide insights into ANS function.

Q3: *What patterns in HRV can be observed in trauma-exposed populations?*

The results of this thesis show PTSD can manifest within the body. This is evident when comparing HRV of individuals with PTSD and without. According to current research, individuals with psychiatric disorders such as PTSD show *reduced* HRV compared to healthy individuals (see section 3). In this thesis specifically, patients who suffer from Post Traumatic Stress Disorder exhibited significantly *lower* LF and HF power as well as in some cases even TP and $pNN50$, compared to healthy controls. Unfortunately, not all HRV metrics corresponded as anticipated. Some time-domain and non-linear measurements as well as frequency-domain parameters did not show any noteworthy effects, when comparing the overall HRV of both groups. *Nonetheless, this thesis suggests that a significant reduction in LF and HF power is a signature for emotional distress and trauma.*

Q4: *How feasible is the detection of trauma signatures during clinical applications?*

Ultimately, the outcomes of this thesis support the idea of HRV, particularly LF and HF , to be a useful tool to not only assess longterm effects of PTSD on overall health, but also to show short-term effects of stress response and stress relief. Specifically, this research showed many significant differences in HRV between the two groups through UST analyses of below 5 min segments. Even in very short time frames of around 30 seconds there were significant and promising findings. However, an extensive evaluation of the effectiveness of such UST analyses for real-time monitoring was not

managed fully in this work and is therefore still open and needed. Furthermore, the sole use of HRV as a diagnostic tool to distinct PTSD from other psychiatric conditions is still insufficient. Therefore, with further investigation, development and research, HRV in conjunction with other medical diagnostics could possibly be used as a biomarker to detect trauma signatures in and during clinical applications.

Potential research directions. These findings pave the way for further research in trauma detection applications. Specifically, the potential of Heart Rate Variability (HRV) emerges as a critical research direction. HRV can be explored not only as an objective measure of the therapeutic effect within interventions like EMDR, but also as a quantifiable measure of trauma load and physiological stress.

Integrating this into clinical practice could make it potentially feasible for real-time monitoring of trauma responses. Moreover, with the identified features and physiological patterns, future studies may explore the development of predictive machine learning models further. This could substantially improve trauma care through the early and objective detection of trauma signatures within therapeutic interventions.

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Appendices

A Result Tables

HRV metric	PTSD (n=31)	Healthy Control (n=29)	p-value
Mean HR	80.31 $\pm$ 7.90	79.51 $\pm$ 10.63	0.8824
SDNN	64.88 $\pm$ 35.64	72.13 $\pm$ 42.56	0.2547
RMSSD	52.39 $\pm$ 41.65	66.12 $\pm$ 55.45	0.1644
pNN50	12.00 $\pm$ 16.35	15.03 $\pm$ 19.30	0.8129
VLF	1124.59 $\pm$ 1653.29	11119.65 $\pm$ 55319.78	0.7561
LF	1150.92 $\pm$ 2244.20	10170.66 $\pm$ 48538.23	0.0545
HF	1266.63 $\pm$ 2864.43	2011.51 $\pm$ 3106.34	0.0332*
TP	3542.14 $\pm$ 6607.56	23301.83 $\pm$ 106187.95	0.1352
LF/HF Ratio	1.48 $\pm$ 0.79	2.02 $\pm$ 3.36	0.7448
Log LF	6.46 $\pm$ 0.95	7.01 $\pm$ 1.27	0.0545
Log HF	6.21 $\pm$ 1.17	6.78 $\pm$ 1.28	0.0332*
HFnu	44.15 $\pm$ 13.64	45.39 $\pm$ 17.72	0.7448
LFnu	55.85 $\pm$ 13.64	54.61 $\pm$ 17.72	0.7448
SD1	37.04 $\pm$ 29.45	46.75 $\pm$ 39.21	0.1644
SD2	81.20 $\pm$ 39.29	89.13 $\pm$ 48.52	0.3074
SD1/SD2 Ratio	2.61 $\pm$ 1.01	2.35 $\pm$ 0.80	0.4595
SampEn	1.18 $\pm$ 0.34	1.19 $\pm$ 0.34	0.9528

TABLE 7: HRV results entire signal (~ 15 min) presented as: Mean $\pm$ (Std).

*Statistically significant ($p < 0.05$).

HRV metric	Healthy Control (n=29)	PTSD (n=31)	p-value
Mean HR	80.64 $\pm$ 11.11	81.72 $\pm$ 7.93	0.6254
SDNN	64.44 $\pm$ 34.12	63.84 $\pm$ 47.84	0.4075
RMSSD	56.91 $\pm$ 56.89	54.37 $\pm$ 58.03	0.6679
pNN50	14.87 $\pm$ 19.52	10.93 $\pm$ 15.98	0.5103
VLF	1206.12 $\pm$ 742.81	1492.75 $\pm$ 1564.97	0.6465
LF	1390.49 $\pm$ 2405.42	797.44 $\pm$ 712.51	0.2672
HF	1947.10 $\pm$ 4044.84	715.01 $\pm$ 960.97	0.1831
TP	4543.70 $\pm$ 6591.90	3005.20 $\pm$ 2712.14	0.4686
LF/HF Ratio	1.77 $\pm$ 1.18	2.00 $\pm$ 1.38	0.5740
Log LF	6.66 $\pm$ 0.92	6.31 $\pm$ 0.91	0.2672
Log HF	6.41 $\pm$ 1.38	5.84 $\pm$ 1.26	0.1831
HFnu	43.32 $\pm$ 19.56	39.37 $\pm$ 15.41	0.5740
LFnu	56.68 $\pm$ 19.56	60.63 $\pm$ 15.41	0.5740
SD1	40.24 $\pm$ 40.23	38.44 $\pm$ 41.02	0.6679
SD2	79.43 $\pm$ 32.68	77.04 $\pm$ 46.18	0.3669
SD1/SD2 Ratio	2.73 $\pm$ 1.09	2.72 $\pm$ 1.22	0.7448
SampEn	1.26 $\pm$ 0.31	1.21 $\pm$ 0.37	0.8824

TABLE 8: HRV results 1st window (5 min) presented as: Mean $\pm$ (Std).*Statistically significant ($p < 0.05$).

HRV metric	Healthy Control (n=29)	PTSD (n=31)	p-value
Mean HR	80.86 $\pm$ 11.22	81.92 $\pm$ 8.12	0.6046
SDNN	67.99 $\pm$ 37.56	61.67 $\pm$ 49.70	0.1644
RMSSD	61.84 $\pm$ 62.77	50.95 $\pm$ 49.86	0.4075
pNN50	15.30 $\pm$ 19.53	11.01 $\pm$ 15.15	0.4373
VLF	1221.83 $\pm$ 734.60	1454.75 $\pm$ 1628.83	0.4244
LF	1012.61 $\pm$ 1117.60	637.56 $\pm$ 592.71	0.0509
HF	1508.44 $\pm$ 2994.84	696.52 $\pm$ 998.71	0.0412*
TP	3742.88 $\pm$ 3643.99	2788.84 $\pm$ 2621.38	0.0889
LF/HF Ratio	1.42 $\pm$ 0.81	1.94 $\pm$ 1.54	0.4595
Log LF	6.56 $\pm$ 0.80	6.06 $\pm$ 0.94	0.0509
Log HF	6.46 $\pm$ 1.21	5.70 $\pm$ 1.39	0.0412*
HFnu	46.65 $\pm$ 18.07	42.08 $\pm$ 18.03	0.4595
LFnu	53.35 $\pm$ 18.07	57.92 $\pm$ 18.03	0.4595
SD1	43.73 $\pm$ 44.39	36.01 $\pm$ 35.19	0.4075
SD2	83.02 $\pm$ 35.34	74.08 $\pm$ 44.26	0.1471
SD1/SD2 Ratio	2.66 $\pm$ 1.06	2.67 $\pm$ 1.21	0.7448
SampEn	1.25 $\pm$ 0.37	1.25 $\pm$ 0.38	0.7673

TABLE 9: HRV results 1st window (3 min) presented as: Mean $\pm$ (Std).

*Statistically significant ($p < 0.05$).

HRV metric	Healthy Control (n=29)	PTSD (n=31)	p-value
Mean HR	79.09 $\pm$ 10.52	79.71 $\pm$ 8.10	1.0000
SDNN	77.56 $\pm$ 66.04	60.33 $\pm$ 28.13	0.2609
RMSSD	74.90 $\pm$ 75.07	50.75 $\pm$ 35.55	0.1391
pNN50	15.38 $\pm$ 18.85	13.15 $\pm$ 17.74	0.7226
VLF	48561.30 $\pm$ 252586.17	1652.22 $\pm$ 1456.39	0.3289
LF	34583.92 $\pm$ 177433.43	1059.83 $\pm$ 1092.94	0.0784
HF	4021.22 $\pm$ 9740.53	1224.28 $\pm$ 1676.68	0.2033
TP	87166.45 $\pm$ 438953.67	3936.34 $\pm$ 3571.73	0.2251
LF/HF Ratio	2.00 $\pm$ 3.48	1.35 $\pm$ 0.98	0.7673
Log LF	7.19 $\pm$ 1.59	6.59 $\pm$ 0.87	0.0784
Log HF	7.03 $\pm$ 1.48	6.50 $\pm$ 1.07	0.2033
HFnu	47.38 $\pm$ 18.01	48.28 $\pm$ 15.27	0.7673
LFnu	52.62 $\pm$ 18.01	51.72 $\pm$ 15.27	0.7673
SD1	52.96 $\pm$ 53.08	35.89 $\pm$ 25.14	0.1391
SD2	94.71 $\pm$ 78.36	76.51 $\pm$ 32.83	0.3748
SD1/SD2 Ratio	2.15 $\pm$ 0.67	2.42 $\pm$ 0.79	0.1880
SampEn	1.16 $\pm$ 0.36	1.21 $\pm$ 0.30	0.5540

TABLE 10: HRV results last window (5 min) presented as: Mean $\pm$ (Std).*Statistically significant ($p < 0.05$).

HRV metric	Healthy Control (n=29)	PTSD (n=31)	p-value
Mean HR	78.02 $\pm$ 10.57	78.55 $\pm$ 8.84	0.9646
SDNN	55.65 $\pm$ 28.93	49.95 $\pm$ 28.86	0.2033
RMSSD	50.14 $\pm$ 42.40	41.08 $\pm$ 36.69	0.6572
pNN50	15.27 $\pm$ 20.81	12.70 $\pm$ 17.36	0.9469
VLF	931.59 $\pm$ 737.05	868.01 $\pm$ 867.56	0.3748
LF	1181.56 $\pm$ 1870.33	860.02 $\pm$ 1295.39	0.1391
HF	1622.58 $\pm$ 4027.29	1008.23 $\pm$ 2160.23	0.4159
TP	3735.74 $\pm$ 6262.90	2736.26 $\pm$ 3634.01	0.1735
LF/HF Ratio	1.84 $\pm$ 1.24	1.72 $\pm$ 1.30	0.6787
Log LF	6.56 $\pm$ 0.95	6.14 $\pm$ 1.11	0.1391
Log HF	6.22 $\pm$ 1.38	5.93 $\pm$ 1.25	0.4159
HFnu	42.40 $\pm$ 18.48	44.21 $\pm$ 19.37	0.6787
LFnu	57.60 $\pm$ 18.48	55.79 $\pm$ 19.37	0.6787
SD1	35.45 $\pm$ 29.98	29.05 $\pm$ 25.95	0.6572
SD2	68.82 $\pm$ 31.05	63.31 $\pm$ 33.29	0.2308
SD1/SD2 Ratio	2.61 $\pm$ 1.10	2.62 $\pm$ 1.00	0.8941
SampEn	1.37 $\pm$ 0.41	1.40 $\pm$ 0.34	0.5944

TABLE 11: HRV results last window (3 min) presented as: Mean $\pm$ (Std).

*Statistically significant ($p < 0.05$).

HRV metric	Healthy Control (n=29)	PTSD (n=31)	p-value
Mean HR	78.26 $\pm$ 10.59	78.26 $\pm$ 9.16	0.8707
SDNN	54.71 $\pm$ 30.49	47.69 $\pm$ 25.23	0.2737
RMSSD	48.48 $\pm$ 43.44	40.41 $\pm$ 34.77	0.6679
pNN50	15.24 $\pm$ 21.29	12.61 $\pm$ 17.06	0.9645
VLF	975.88 $\pm$ 1169.22	848.18 $\pm$ 859.97	0.5640
LF	1550.22 $\pm$ 4006.02	688.18 $\pm$ 675.63	0.1431
HF	2539.51 $\pm$ 8126.83	862.86 $\pm$ 1589.32	0.2609
TP	5065.61 $\pm$ 13007.06	2399.22 $\pm$ 2334.81	0.2609
LF/HF Ratio	1.95 $\pm$ 2.39	1.88 $\pm$ 1.57	0.7787
Log LF	6.51 $\pm$ 1.10	6.02 $\pm$ 1.10	0.1431
Log HF	6.32 $\pm$ 1.52	5.85 $\pm$ 1.26	0.2609
HFnu	45.74 $\pm$ 21.27	45.25 $\pm$ 22.78	0.7787
LFnu	54.26 $\pm$ 21.27	54.75 $\pm$ 22.78	0.7787
SD1	34.28 $\pm$ 30.72	28.57 $\pm$ 24.58	0.6679
SD2	67.87 $\pm$ 32.98	59.63 $\pm$ 28.54	0.2936
SD1/SD2 Ratio	2.65 $\pm$ 1.11	2.58 $\pm$ 1.02	0.9646
SampEn	1.42 $\pm$ 0.51	1.41 $\pm$ 0.33	0.7005

TABLE 12: HRV results last window (2 min) presented as: Mean $\pm$ (Std).*Statistically significant ($p < 0.05$).

HRV metric	Healthy Control (n=29)	PTSD (n=31)	p-value
Mean HR	79.86 $\pm$ 10.71	80.72 $\pm$ 7.76	0.8359
SDNN	70.97 $\pm$ 41.13	62.08 $\pm$ 34.90	0.2033
RMSSD	65.68 $\pm$ 55.41	52.56 $\pm$ 41.59	0.1831
pNN50	15.15 $\pm$ 18.99	12.04 $\pm$ 16.57	0.6787
VLF	24901.04 $\pm$ 126261.98	1572.49 $\pm$ 1423.57	0.3514
LF	17994.05 $\pm$ 88629.94	928.64 $\pm$ 846.13	0.0491*
HF	2988.00 $\pm$ 5566.16	969.65 $\pm$ 1248.14	0.0711
TP	45883.08 $\pm$ 219257.30	3470.77 $\pm$ 3025.38	0.1069
LF/HF Ratio	1.89 $\pm$ 1.86	1.68 $\pm$ 0.96	0.8591
Log LF	6.94 $\pm$ 0.93	6.45 $\pm$ 0.81	0.0526
Log HF	6.73 $\pm$ 1.24	6.17 $\pm$ 1.05	0.0623
HFnu	45.12 $\pm$ 15.79	43.82 $\pm$ 13.03	0.9293
LFnu	54.88 $\pm$ 15.79	56.18 $\pm$ 13.03	0.9293
SD1	46.44 $\pm$ 39.18	37.16 $\pm$ 29.41	0.1831
SD2	87.10 $\pm$ 45.82	76.78 $\pm$ 37.55	0.2308
SD1/SD2 Ratio	2.45 $\pm$ 0.76	2.57 $\pm$ 0.83	0.6254
SampEn	1.21 $\pm$ 0.29	1.21 $\pm$ 0.30	0.7005

TABLE 13: HRV results full windowed wnalysis (5 min) presented as: Mean $\pm$ (Std).

*Statistically significant ($p < 0.05$).

HRV metric	Healthy Control (n=29)	PTSD (n=31)	p-value
Mean HR	79.56 $\pm$ 10.64	80.28 $\pm$ 7.89	0.8824
SDNN	65.73 $\pm$ 33.91	57.42 $\pm$ 30.98	0.1735
RMSSD	60.42 $\pm$ 47.68	48.72 $\pm$ 37.64	0.1689
pNN50	15.19 $\pm$ 19.35	12.15 $\pm$ 16.58	0.7226
VLF	11546.75 $\pm$ 56011.44	1864.88 $\pm$ 4139.03	0.5344
LF	8825.58 $\pm$ 41258.92	1639.15 $\pm$ 4720.55	0.0759
HF	2045.56 $\pm$ 3265.83	2000.34 $\pm$ 6319.13	0.1644
TP	22417.89 $\pm$ 99430.42	5504.38 $\pm$ 15080.01	0.1880
LF/HF Ratio	1.82 $\pm$ 1.20	1.85 $\pm$ 1.09	0.8359
Log LF	6.65 $\pm$ 0.76	6.25 $\pm$ 0.90	0.0666
Log HF	6.43 $\pm$ 1.18	5.97 $\pm$ 1.15	0.0976
HFnu	44.96 $\pm$ 16.42	43.54 $\pm$ 14.57	0.8941
LFnu	55.04 $\pm$ 16.42	56.46 $\pm$ 14.57	0.8941
SD1	42.72 $\pm$ 33.72	34.44 $\pm$ 26.61	0.1689
SD2	80.67 $\pm$ 37.00	71.08 $\pm$ 34.01	0.2140
SD1/SD2 Ratio	2.56 $\pm$ 0.80	2.64 $\pm$ 0.76	0.7226
SampEn	1.28 $\pm$ 0.29	1.28 $\pm$ 0.28	0.8475

TABLE 14: HRV results full windowed analysis (3 min) presented as: Mean $\pm$ (Std).*Statistically significant ($p < 0.05$).

B Visuals

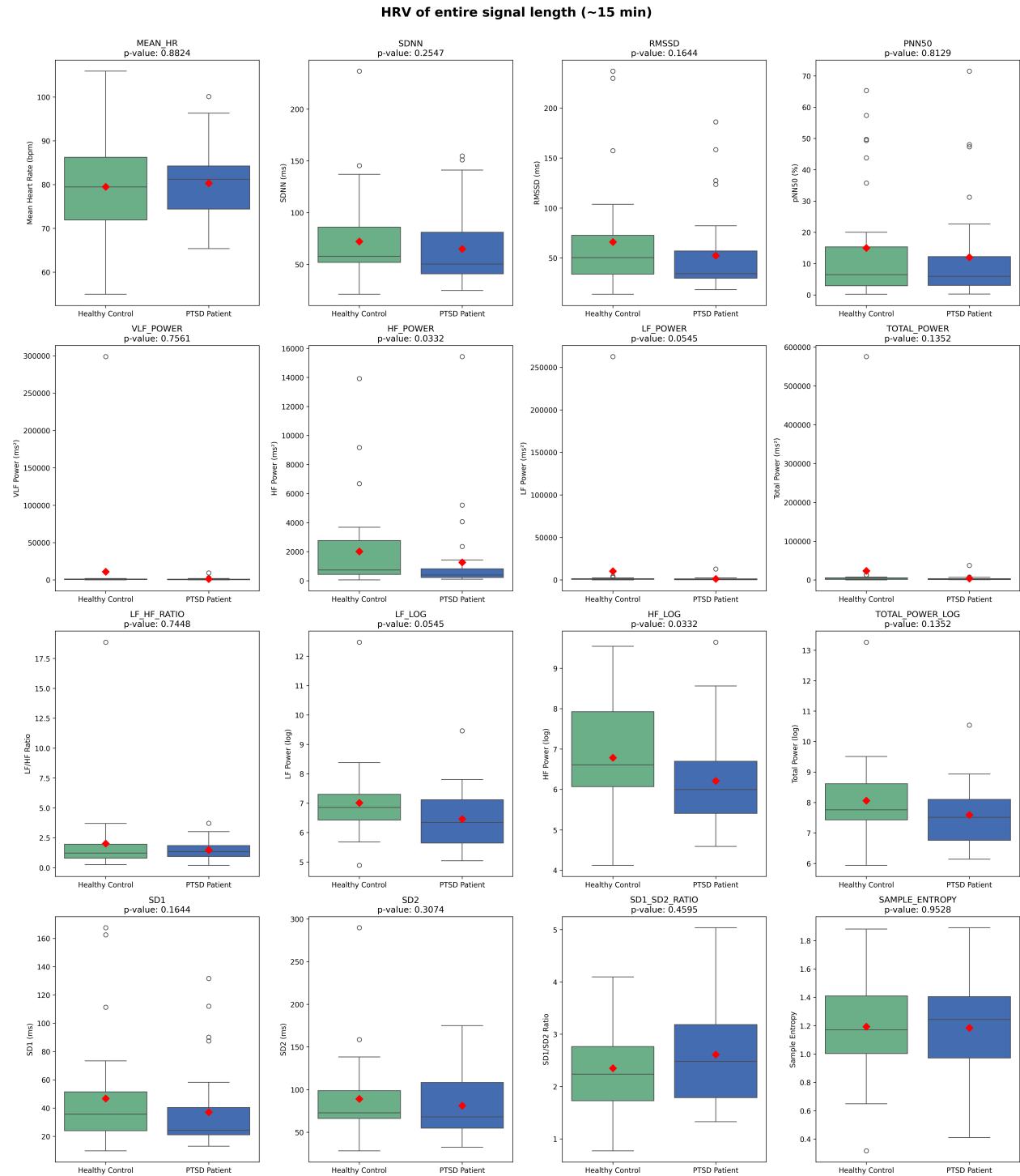


FIGURE 23: HRV comparison for the entire signal length (15 min)

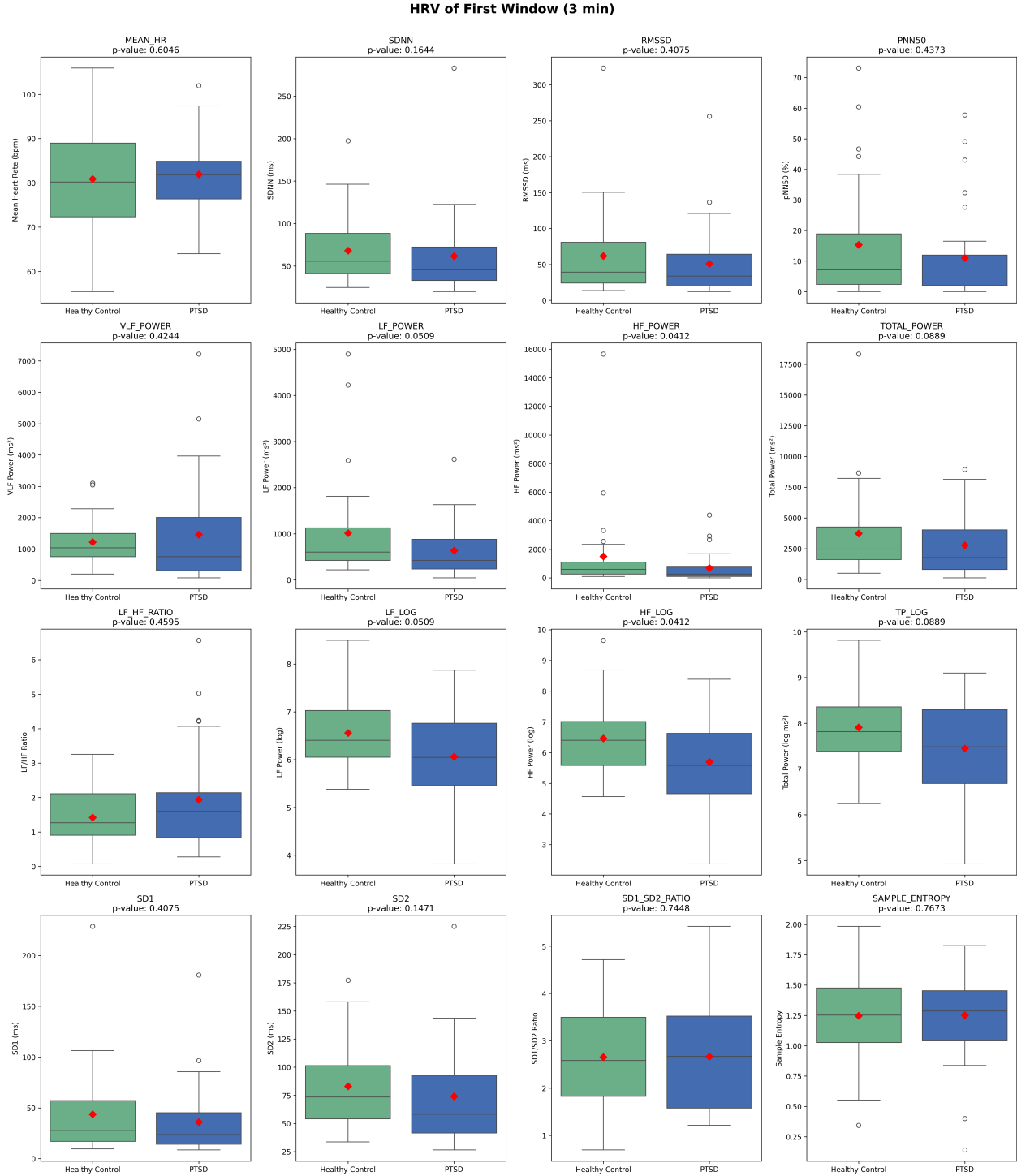


FIGURE 24: HRV comparison for the first 3 min window

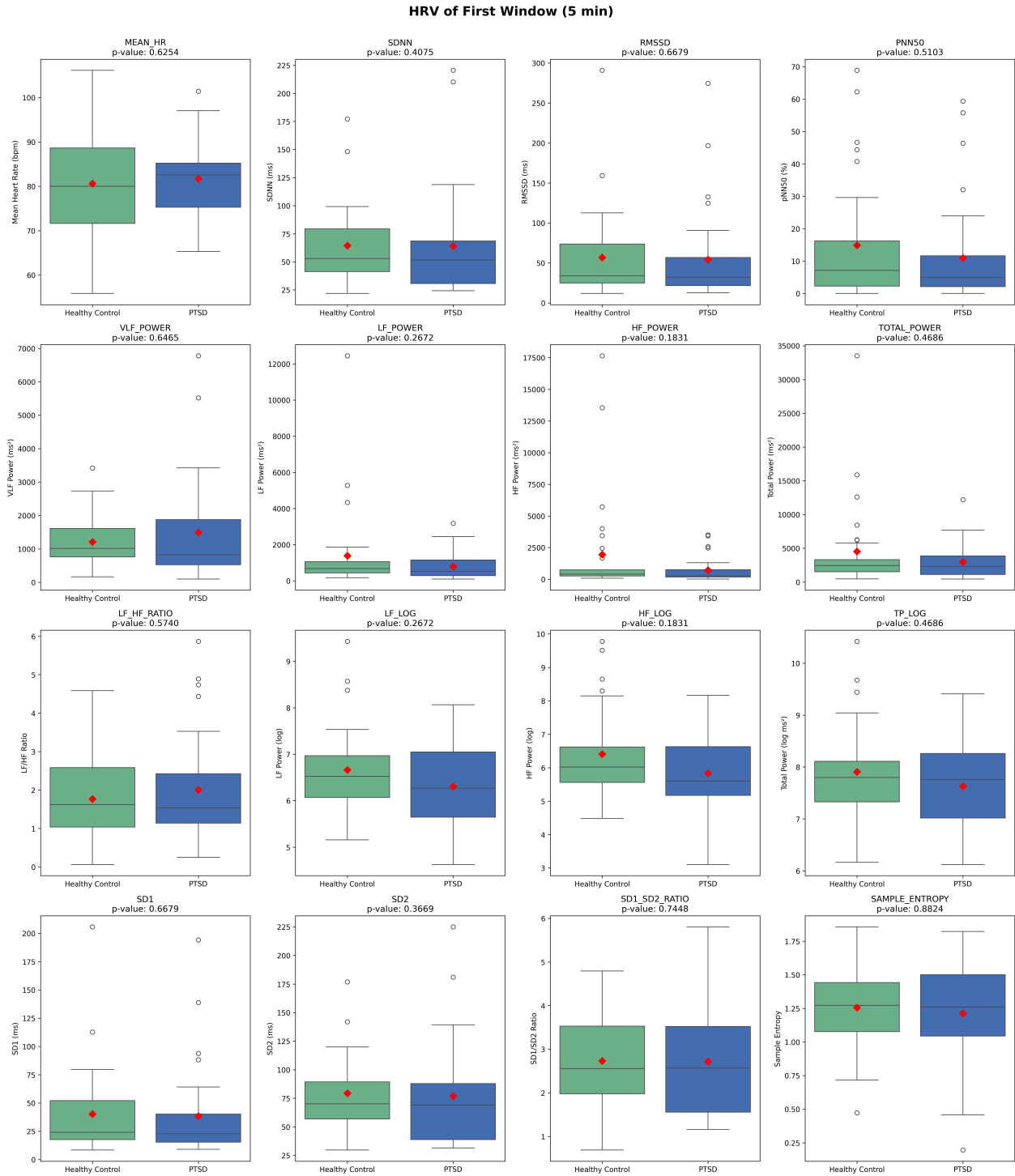


FIGURE 25: HRV comparison for the first 5 min Window

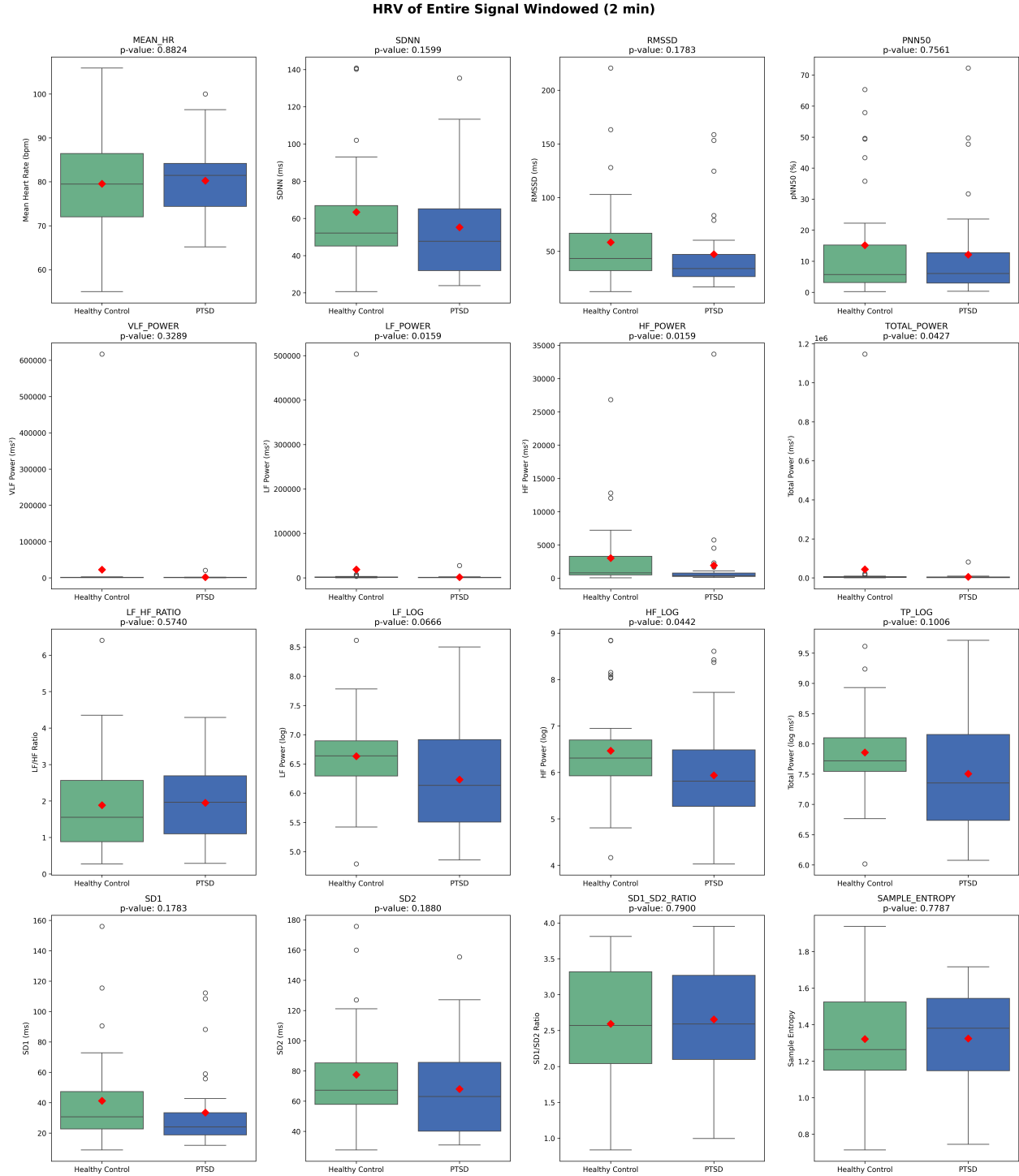


FIGURE 26: HRV comparison of entire signal windowed (2 min)

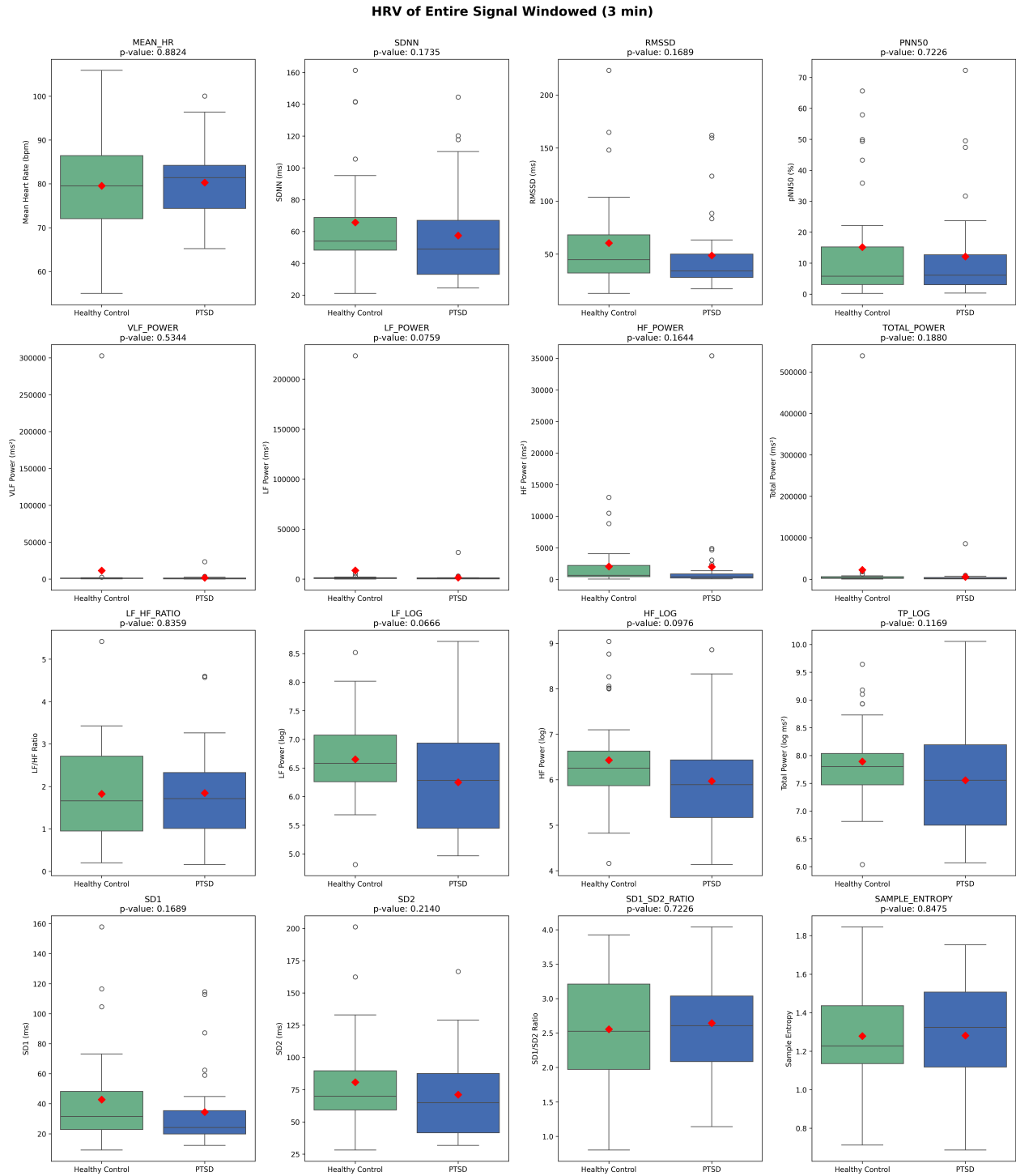


FIGURE 27: HRV comparison of entire signal windowed (3 min)

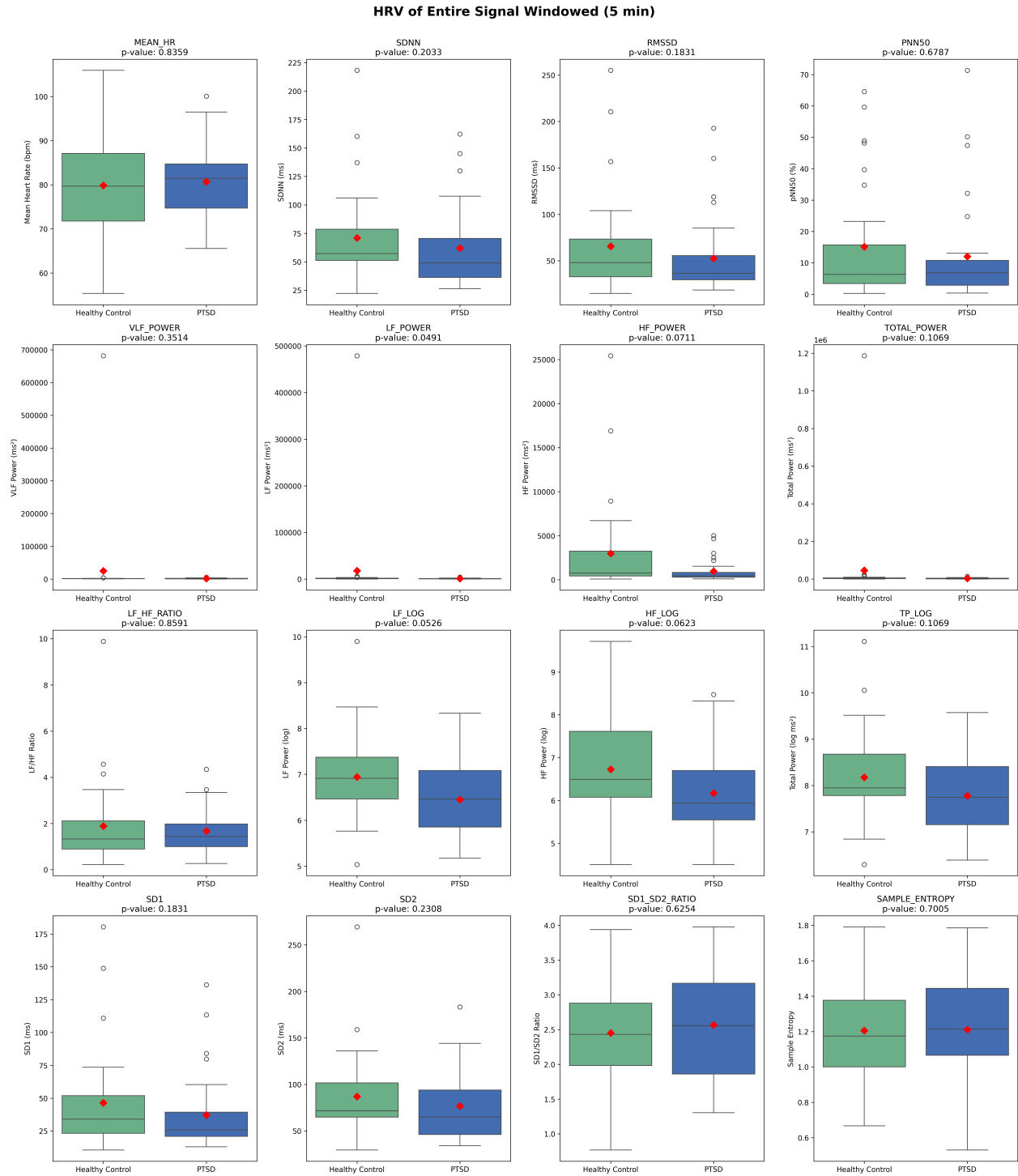


FIGURE 28: HRV comparison of entire signal windowed (5 min)

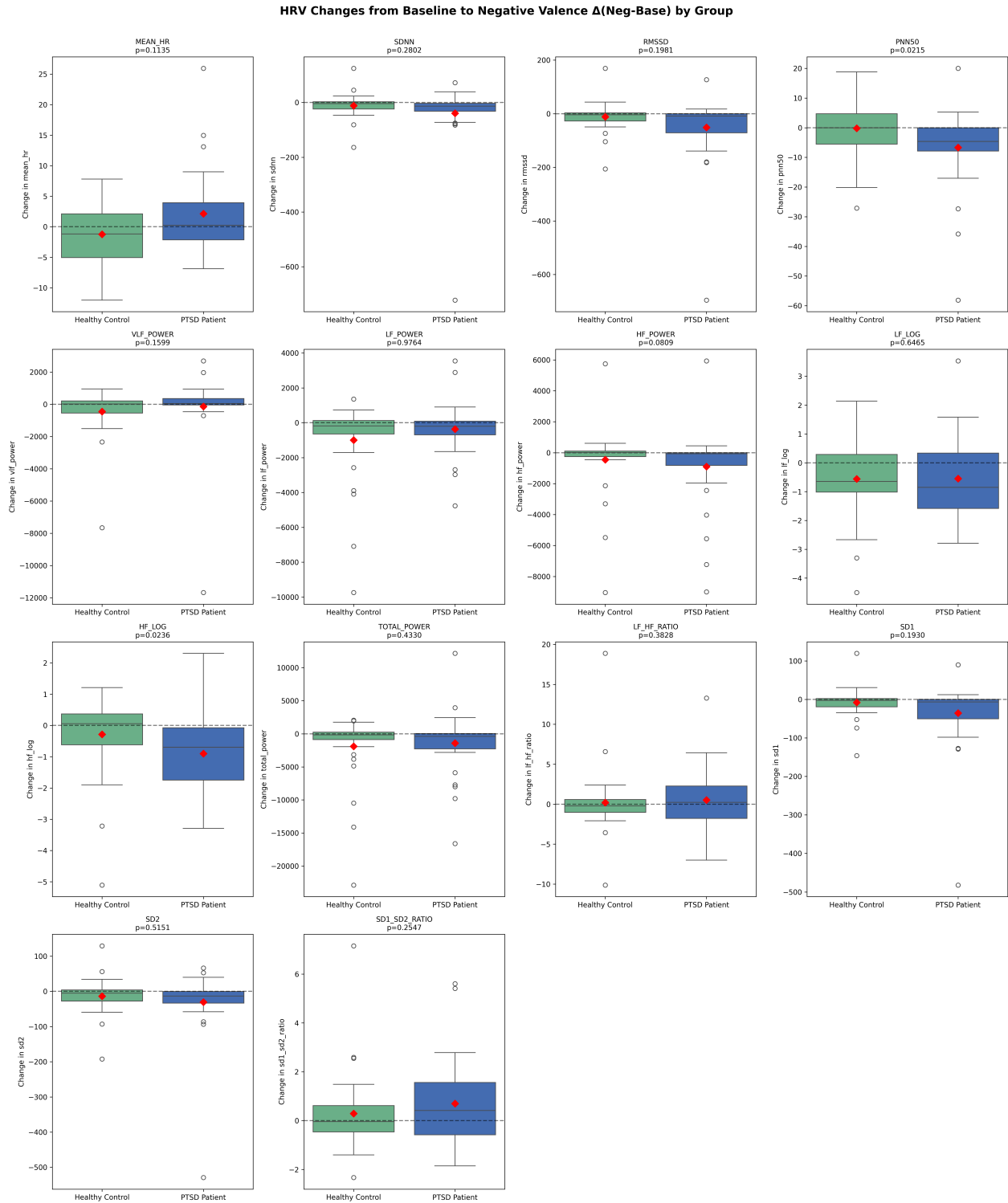


FIGURE 29: Change in HRV from baseline to negative valence (Δ Neg-Base)

C Source Code

LISTING 1: HRV analysis pipeline folder processing: `ecg_batch.ipynb`

```

1  import pandas as pd
2  import numpy as np
3  import neurokit2 as nk
4  import pyhrv.time_domain as td
5  import pyhrv.frequency_domain as fd
6  import pyhrv.tools as tools
7  import pyhrv.nonlinear as nl
8  from scipy.signal import butter, filtfilt, iirnotch
9  import glob
10 import os
11
12 csv_folder = '../CSV'
13
14 csv_files = glob.glob(os.path.join(csv_folder, '*.csv'))
15
16 for csv_path in csv_files:
17     filename = os.path.basename(csv_path)
18     name = filename.replace('.csv', '')
19
20     patient = 1 if name.startswith('P') else 0
21
22     try:
23         df = pd.read_csv(csv_path, delimiter=';', skiprows=1)
24
25         df.columns = ['Nr', 'Marker', 'Puls', 'Startle', 'EKG', 'EDA', 'Zygomaticus',
26                      'Digital_0', 'Digital_1', 'Digital_2', 'Digital_3']
27
28         ecg = df['EKG']
29         digital_2 = df['Digital_2']
30
31         sampling_rate = 2000.0
32         time_seconds = np.arange(len(ecg)) / sampling_rate
33         time_minutes = time_seconds / 60
34
35         def find_digital_events(digital_channel, channel_name):
36             events = []
37
38             diff = np.diff(digital_channel)
39             change_indices = np.where(diff != 0)[0] + 1
40
41             for idx in change_indices:
42                 timestamp = time_seconds[idx]
43                 old_value = digital_channel.iloc[idx-1]
44                 new_value = digital_channel.iloc[idx]
45                 events.append({
46                     'channel': channel_name,
47                     'timestamp': timestamp,
48                     'sample_index': idx,
49                     'old_value': old_value,
50                     'new_value': new_value,
51                 })

```

```

52
53     return events
54
55     digital_2_events = find_digital_events(digital_2, 'Digital_2')
56
57     if len(digital_2_events) >= 22:
58         first_event_idx = digital_2_events[0]['sample_index']
59         last_event_idx = digital_2_events[-1]['sample_index']
60
61         ecg_trimmed = ecg.iloc[first_event_idx:last_event_idx+1]
62         time_trimmed = time_seconds[first_event_idx:last_event_idx+1]
63
64     else:
65         ecg_trimmed = ecg
66         time_trimmed = time_seconds
67
68     time_trimmed_reset = np.arange(len(ecg_trimmed)) / sampling_rate
69
70     def notch_filter(data, notch_freq=50, fs=360, quality_factor=30):
71         from scipy.signal import iirnotch, filtfilt
72         b, a = iirnotch(notch_freq, quality_factor, fs)
73         filtered_data = filtfilt(b, a, data)
74         return filtered_data
75
76     def butter_bandpass(lowcut, highcut, fs, order=4):
77         from scipy.signal import butter
78         nyq = 0.5 * fs
79         low = lowcut / nyq
80         high = highcut / nyq
81         b, a = butter(order, [low, high], btype='band')
82         return b, a
83
84     def butter_bandpass_filter(data, lowcut, highcut, fs, order=4):
85         from scipy.signal import filtfilt
86         b, a = butter_bandpass(lowcut, highcut, fs, order=order)
87         y = filtfilt(b, a, data)
88         return y
89
90     notch_filtered = notch_filter(ecg_trimmed, notch_freq=50, fs=sampling_rate,
91                                   quality_factor=30)
92     ecg_cleaned = butter_bandpass_filter(notch_filtered, 5, 35, sampling_rate, order=4)
93
94     _, rpeaks = nk.ecg_peaks(ecg_cleaned, sampling_rate=sampling_rate)
95     r_peaks_indices = rpeaks['ECG_R_Peaks']
96
97
98     rr_intervals = np.diff(r_peaks_indices) / sampling_rate * 1000
99
100    def window_rr_intervals(rr_intervals, r_peaks_indices, sampling_rate,
101                            window_duration_sec=120, overlap_sec=0):
102        windows = []
103
104        r_peak_times = r_peaks_indices / sampling_rate
105
106        total_duration = r_peak_times[-1] - r_peak_times[0]

```

```

107     window_start_times = []
108
109     current_start = 0
110     while current_start + window_duration_sec <= total_duration:
111         window_start_times.append(current_start)
112         current_start += (window_duration_sec - overlap_sec)
113
114     for i, start_time in enumerate(window_start_times):
115         end_time = start_time + window_duration_sec
116
117         window_mask = (r_peak_times >= start_time) & (r_peak_times < end_time)
118         window_r_peaks = r_peaks_indices[window_mask]
119
120         if len(window_r_peaks) < 2:
121             continue
122
123         window_rr = np.diff(window_r_peaks) / sampling_rate * 1000
124
125         windows.append({
126             'window_id': i + 1,
127             'start_time': start_time,
128             'end_time': end_time,
129             'rr_intervals': window_rr,
130             'n_peaks': len(window_r_peaks),
131             'n_intervals': len(window_rr),
132         })
133
134     return windows
135
136 if len(rr_intervals) > 0:
137     windowed_data = window_rr_intervals(rr_intervals, r_peaks_indices, sampling_rate)
138 else:
139     windowed_data = []
140     continue
141
142 def calculate_hrv_metrics(rr_intervals, window_id):
143
144     results = {
145         'name': name,
146         'patient': patient,
147         'window_id': window_id,
148     }
149
150     try:
151
152         hr_result = td.hr_parameters(rr_intervals)
153         results['mean_hr'] = hr_result['hr_mean']
154
155         sdn_result = td.sdn(rr_intervals)
156         results['sdnn'] = sdn_result['sdnn']
157
158         rmssd_result = td.rmssd(rr_intervals)
159         results['rmssd'] = rmssd_result['rmssd']
160
161         pnn50_result = td.pnn50(rr_intervals)

```

```

162         results['pnn50'] = pnn50_result['pnn50']
163
164     except Exception as e:
165         results.update({
166             'mean_hr': np.nan,
167             'sdnn': np.nan, 'rmssd': np.nan, 'pnn50': np.nan
168         })
169
170     try:
171
172         welch_result = fd.welch_psd(rr_intervals, show=False)
173         results['vlf_power'] = welch_result['fft_abs'][0]
174         results['lf_power'] = welch_result['fft_abs'][1]
175         results['hf_power'] = welch_result['fft_abs'][2]
176         results['total_power'] = welch_result['fft_total']
177         results['lf_hf_ratio'] = welch_result['fft_ratio']
178         results['lf_norm'] = welch_result['fft_norm'][0]
179         results['hf_norm'] = welch_result['fft_norm'][1]
180         results['lf_log'] = welch_result['fft_log'][1]
181         results['hf_log'] = welch_result['fft_log'][2]
182
183     except Exception as e:
184         results.update({
185             'vlf_power': np.nan, 'lf_power': np.nan, 'hf_power': np.nan,
186             'total_power': np.nan, 'lf_hf_ratio': np.nan,
187             'lf_norm': np.nan, 'hf_norm': np.nan, 'lf_log': np.nan, 'hf_log': np.nan
188         })
189
190     try:
191
192         poicare_result = nl.poincare(rr_intervals, show=False)
193         results['sd1'] = poicare_result['sd1']
194         results['sd2'] = poicare_result['sd2']
195         results['sd1_sd2_ratio'] = poicare_result['sd_ratio']
196
197     try:
198         sampen_result = nl.sample_entropy(rr_intervals, dim=2, tolerance=None)
199         results['sample_entropy'] = sampen_result['sampen']
200     except Exception as e:
201         results['sample_entropy'] = np.nan
202
203     except Exception as e:
204         results.update({
205             'sd1': np.nan, 'sd2': np.nan, 'sd1_sd2_ratio': np.nan,
206             'sample_entropy': np.nan
207         })
208
209     return results
210
211 if len(windowed_data) > 0:
212
213     all_hrv_results = []
214
215     for window_data in windowed_data:
216         window_id = window_data['window_id']

```

```

217         rr_intervals_window = window_data['rr_intervals']
218
219         hrv_results = calculate_hrv_metrics(rr_intervals_window, window_id)
220
221         hrv_results.update({
222             'start_time': window_data['start_time'],
223             'end_time': window_data['end_time'],
224         })
225
226         all_hrv_results.append(hrv_results)
227
228         hrv_df = pd.DataFrame(all_hrv_results)
229
230     else:
231         continue
232
233
234     if len(rr_intervals) > 0:
235
236         overall_hrv_results = calculate_hrv_metrics(rr_intervals, 0)
237
238         overall_hrv_results.update({
239             'total_duration': len(ecg_trimmed) / sampling_rate,
240             'total_rr_intervals': len(rr_intervals),
241         })
242
243         overall_df = pd.DataFrame([overall_hrv_results])
244
245     else:
246         continue
247
248     windowed_csv_path = 'hrv_windowed_results_1min.csv'
249     overall_csv_path = 'hrv_overall_results_1min.csv'
250
251
252     if len(windowed_data) > 0 and not hrv_df.empty:
253         file_exists = os.path.exists(windowed_csv_path)
254
255         hrv_df.to_csv(windowed_csv_path,
256                       mode='a',
257                       header=not file_exists,
258                       index=False)
259
260     if len(rr_intervals) > 0:
261         file_exists = os.path.exists(overall_csv_path)
262
263         overall_df.to_csv(overall_csv_path,
264                           mode='a',
265                           header=not file_exists,
266                           index=False)
267
268     except Exception as e:
269         continue

```

LISTING 2: HRV analysis pipeline single signal processing: `ecg_single.ipynb`

```

1  import pandas as pd
2  import numpy as np
3  import neurokit2 as nk
4  import pyhrv.time_domain as td
5  import pyhrv.frequency_domain as fd
6  import pyhrv.tools as tools
7  import pyhrv.nonlinear as nl
8  from scipy.signal import butter, filtfilt, iirnotch
9
10 import os
11
12 name = 'K01'
13 patient = 0 # 0 for control, 1 for patient
14 df = pd.read_csv(f'../CSV/{name}.csv', delimiter=';', skiprows=1)
15
16 df.columns = ['Nr', 'Marker', 'Puls', 'Startle', 'EKG', 'EDA', 'Zygomaticus',
17               'Digital_0', 'Digital_1', 'Digital_2', 'Digital_3']
18
19 ecg = df['EKG']
20 digital_2 = df['Digital_2']
21
22 sampling_rate = 2000.0
23 time_seconds = np.arange(len(ecg)) / sampling_rate
24 time_minutes = time_seconds / 60
25
26 def find_digital_events(digital_channel, channel_name):
27     events = []
28
29     diff = np.diff(digital_channel)
30     change_indices = np.where(diff != 0)[0] + 1
31
32     for idx in change_indices:
33         timestamp = time_seconds[idx]
34         old_value = digital_channel.iloc[idx-1]
35         new_value = digital_channel.iloc[idx]
36         events.append({
37             'channel': channel_name,
38             'timestamp': timestamp,
39             'sample_index': idx,
40             'old_value': old_value,
41             'new_value': new_value,
42         })
43
44     return events
45
46 digital_2_events = find_digital_events(digital_2, 'Digital_2')
47
48 if len(digital_2_events) >= 22:
49     first_event_idx = digital_2_events[0]['sample_index']
50     last_event_idx = digital_2_events[-1]['sample_index']
51
52     ecg_trimmed = ecg.iloc[first_event_idx:last_event_idx+1]
53     time_trimmed = time_seconds[first_event_idx:last_event_idx+1]
54

```

```

55     trimmed_duration = time_seconds[last_event_idx] - time_seconds[first_event_idx]
56
57 else:
58     ecg_trimmed = ecg
59     time_trimmed = time_seconds
60
61 time_trimmed_reset = np.arange(len(ecg_trimmed)) / sampling_rate
62
63 def notch_filter(data, notch_freq=50, fs=360, quality_factor=30):
64     b, a = iirnotch(notch_freq, quality_factor, fs)
65
66     filtered_data = filtfilt(b, a, data)
67     return filtered_data
68
69
70 def butter_bandpass(lowcut, highcut, fs, order=4):
71     nyq = 0.5 * fs
72     low = lowcut / nyq
73     high = highcut / nyq
74     b, a = butter(order, [low, high], btype='band')
75     return b, a
76
77 def butter_bandpass_filter(data, lowcut, highcut, fs, order=4):
78     b, a = butter_bandpass(lowcut, highcut, fs, order=order)
79     y = filtfilt(b, a, data)
80     return y
81
82 notch_filtered = notch_filter(ecg_trimmed, notch_freq=50, fs=sampling_rate,
83                               quality_factor=30)
84 ecg_cleaned = butter_bandpass_filter(notch_filtered, 5, 35, sampling_rate, order=4)
85
86 try:
87     _, rpeaks = nk.ecg_peaks(ecg_cleaned, sampling_rate=sampling_rate)
88     r_peaks_indices = rpeaks['ECG_R_Peaks']
89
90     rr_intervals = np.diff(r_peaks_indices) / sampling_rate * 1000
91
92 except Exception as e:
93     r_peaks_indices = []
94     rr_intervals = []
95
96
97 def window_rr_intervals(rr_intervals, r_peaks_indices, sampling_rate,
98                         window_duration_sec=120, overlap_sec=0):
99
100     windows = []
101
102     r_peak_times = r_peaks_indices / sampling_rate
103
104     total_duration = r_peak_times[-1] - r_peak_times[0]
105     window_start_times = []
106
107     current_start = 0
108     while current_start + window_duration_sec <= total_duration:
109         window_start_times.append(current_start)

```

```

110     current_start += (window_duration_sec - overlap_sec)
111
112     for i, start_time in enumerate(window_start_times):
113         end_time = start_time + window_duration_sec
114
115         window_mask = (r_peak_times >= start_time) & (r_peak_times < end_time)
116         window_r_peaks = r_peaks_indices[window_mask]
117
118         if len(window_r_peaks) < 2:
119             continue
120
121         window_rr = np.diff(window_r_peaks) / sampling_rate * 1000
122
123         windows.append({
124             'window_id': i + 1,
125             'start_time': start_time,
126             'end_time': end_time,
127             'rr_intervals': window_rr,
128             'n_peaks': len(window_r_peaks),
129             'n_intervals': len(window_rr),
130         })
131
132     return windows
133
134
135 if len(rr_intervals) > 0:
136     windowed_data = window_rr_intervals(rr_intervals, r_peaks_indices, sampling_rate)
137 else:
138     windowed_data = []
139
140 def calculate_hrv_metrics(rr_intervals, window_id):
141
142     results = {
143         'name': name,
144         'patient': patient,
145         'window_id': window_id,
146     }
147
148     try:
149         hr_result = td.hr_parameters(rr_intervals)
150         results['mean_hr'] = hr_result['hr_mean']
151
152         sdn_result = td.sdn(rr_intervals)
153         results['sdnn'] = sdn_result['sdnn']
154
155         rmssd_result = td.rmssd(rr_intervals)
156         results['rmssd'] = rmssd_result['rmssd']
157
158         pnn50_result = td.pnn50(rr_intervals)
159         results['pnn50'] = pnn50_result['pnn50']
160
161     except Exception as e:
162         results.update({
163             'mean_hr': np.nan,
164             'sdnn': np.nan, 'rmssd': np.nan, 'pnn50': np.nan

```

```

165     })
166
167     try:
168         welch_result = fd.welch_psd(rr_intervals, show=False)
169         results['vlf_power'] = welch_result['fft_abs'][0]
170         results['lf_power'] = welch_result['fft_abs'][1]
171         results['hf_power'] = welch_result['fft_abs'][2]
172         results['total_power'] = welch_result['fft_total']
173         results['lf_hf_ratio'] = welch_result['fft_ratio']
174         results['lf_norm'] = welch_result['fft_norm'][0]
175         results['hf_norm'] = welch_result['fft_norm'][1]
176         results['lf_log'] = welch_result['fft_log'][1]
177         results['hf_log'] = welch_result['fft_log'][2]
178
179     except Exception as e:
180         results.update({
181             'vlf_power': np.nan, 'lf_power': np.nan, 'hf_power': np.nan,
182             'total_power': np.nan, 'lf_hf_ratio': np.nan,
183             'lf_norm': np.nan, 'hf_norm': np.nan, 'lf_log': np.nan, 'hf_log': np.nan
184         })
185
186     try:
187         poincare_result = nl.poincare(rr_intervals, show=False)
188         results['sd1'] = poincare_result['sd1']
189         results['sd2'] = poincare_result['sd2']
190         results['sd1_sd2_ratio'] = poincare_result['sd_ratio']
191
192     try:
193         sampen_result = nl.sample_entropy(rr_intervals, dim=2, tolerance=None)
194         results['sample_entropy'] = sampen_result['sampen']
195     except Exception as e:
196         results['sample_entropy'] = np.nan
197
198     except Exception as e:
199         results.update({
200             'sd1': np.nan, 'sd2': np.nan, 'sd1_sd2_ratio': np.nan,
201             'sample_entropy': np.nan
202         })
203
204     return results
205
206
207 all_hrv_results = []
208
209 for window_data in windowed_data:
210     window_id = window_data['window_id']
211     rr_intervals_window = window_data['rr_intervals']
212
213     hrv_results = calculate_hrv_metrics(rr_intervals_window, window_id)
214
215     hrv_results.update({
216         'start_time': window_data['start_time'],
217         'end_time': window_data['end_time'],
218     })
219

```

```
220     all_hrv_results.append(hrv_results)
221
222     hrv_df = pd.DataFrame(all_hrv_results)
223
224
225 overall_hrv_results = calculate_hrv_metrics(rr_intervals, 0)
226
227 overall_hrv_results.update({
228     'total_duration': len(ecg_trimmed) / sampling_rate,
229     'total_rr_intervals': len(rr_intervals),
230 })
231
232 overall_df = pd.DataFrame([overall_hrv_results])
233
234 windowed_csv_path = 'hrv_windowed_results.csv'
235 overall_csv_path = 'hrv_overall_results.csv'
236
237 file_exists = os.path.exists(windowed_csv_path)
238
239 hrv_df.to_csv(windowed_csv_path,
240               mode='a',
241               header=not file_exists,
242               index=False)
243
244 file_exists = os.path.exists(overall_csv_path)
245
246 overall_df.to_csv(overall_csv_path,
247                  mode='a',
248                  header=not file_exists,
249                  index=False)
```

LISTING 3: HRV overall analysis visualization: `hrv_overall_analysis.ipynb`

```

1  import pandas as pd
2  import numpy as np
3  import matplotlib.pyplot as plt
4  import seaborn as sns
5  plt.rcParams['figure.dpi'] = 300
6  from scipy import stats
7  import warnings
8  warnings.filterwarnings('ignore')
9
10 df = pd.read_csv('hrv_overall_results.csv')
11
12 df['group'] = df['patient'].map({0: 'Healthy Control', 1: 'PTSD Patient'})
13
14 df['total_power_log'] = np.log(df['total_power'])
15
16 plt.style.use('default')
17 group_colors = {'Healthy Control': '#5EBB86', 'PTSD Patient': '#3267C3'}
18 palette = [group_colors['Healthy Control'], group_colors['PTSD Patient']]
19
20 metrics_info = {
21     'mean_hr': 'Mean Heart Rate (bpm)',
22     'sdnn': 'SDNN (ms)',
23     'rmssd': 'RMSSD (ms)',
24     'pnn50': 'pNN50 (%)',
25     'vlf_power': 'VLF Power (ms2)',
26     'hf_power': 'HF Power (ms2)',
27     'lf_power': 'LF Power (ms2)',
28     'total_power': 'Total Power (ms2)',
29     'lf_hf_ratio': 'LF/HF Ratio',
30     'lf_log': 'LF Power (log)',
31     'hf_log': 'HF Power (log)',
32     'total_power_log': 'Total Power (log)',
33     'sd1': 'SD1 (ms)',
34     'sd2': 'SD2 (ms)',
35     'sd1_sd2_ratio': 'SD1/SD2 Ratio',
36     'sample_entropy': 'Sample Entropy'
37 }
38
39 fig = plt.figure(figsize=(20, 25), dpi=300)
40
41 for i, (metric, ylabel) in enumerate(metrics_info.items(), 1):
42     ax = plt.subplot(4, 4, i)
43
44     sns.boxplot(data=df, x='group', y=metric, ax=ax, palette=palette)
45
46     means = df.groupby('group')[metric].mean()
47     for j, (group, mean_val) in enumerate(means.items()):
48         ax.scatter(j, mean_val, marker='D', s=50, color='red', zorder=10)
49
50     ctrl_data = df[df['patient'] == 0][metric].dropna()
51     ptsd_data = df[df['patient'] == 1][metric].dropna()
52
53     if len(ctrl_data) > 0 and len(ptsd_data) > 0:
54         u_stat, p_val = stats.mannwhitneyu(ctrl_data, ptsd_data, alternative='two-sided')

```

```

55     ax.set_title(f'{metric.upper()}\np-value: {p_val:.4f}')
56
57
58     else:
59         ax.set_title(f'{metric.upper()}')
60
61     ax.set_ylabel(ylabel)
62     ax.set_xlabel('')
63
64
65 plt.tight_layout(rect=[0, 0.03, 1, 0.93])
66 plt.show()
67
68
69 fig_corr = plt.figure(figsize=(12, 10), dpi=300)
70 ax_corr = plt.subplot(1, 1, 1)
71
72 hrv_metrics = ['mean_hr', 'sdnn', 'rmssd', 'pnn50', 'hf_power', 'lf_power', 'total_power', '
73               lf_hf_ratio', 'sd1', 'sd2', 'sd1_sd2_ratio', 'sample_entropy']
74 corr_matrix = df[hrv_metrics].corr()
75
76 sns.heatmap(corr_matrix, annot=True, cmap='coolwarm', center=0, ax=ax_corr, fmt='.2f',
77             cbar_kws={'shrink': 0.8}, square=True, linewidths=0.5)
78 ax_corr.set_title('HRV Metrics Correlation Matrix', fontsize=16, fontweight='bold', pad=20)
79
80 ax_corr.set_xticklabels(ax_corr.get_xticklabels(), rotation=45, ha='right')
81 ax_corr.set_yticklabels(ax_corr.get_yticklabels(), rotation=0)
82
83 plt.tight_layout()
84 plt.show()
85
86
87 fig_effect = plt.figure(figsize=(10, 6), dpi=300)
88 ax_effect = plt.subplot(1, 1, 1)
89
90 key_metrics_plot = ['mean_hr', 'sdnn', 'rmssd', 'pnn50',
91                    'vlf_power', 'lf_power', 'hf_power', 'total_power', 'lf_hf_ratio', 'lf_log'
92                    , 'hf_log', 'hf_norm', 'lf_norm',
93                    'sd1', 'sd2', 'sd1_sd2_ratio', 'sample_entropy']
94
95
96 def cohens_d(group1, group2):
97     n1, n2 = len(group1), len(group2)
98     pooled_std = np.sqrt(((n1 - 1) * group1.var() + (n2 - 1) * group2.var()) / (n1 + n2 - 2))
99     d = (group1.mean() - group2.mean()) / pooled_std
100     return d
101
102 effect_sizes = []
103 for metric in key_metrics_plot:
104     healthy = df[df['patient'] == 0][metric].dropna()
105     ptsd = df[df['patient'] == 1][metric].dropna()
106
107     if len(healthy) > 0 and len(ptsd) > 0:
108         d = cohens_d(healthy, ptsd)
109         effect_sizes.append(abs(d))

```

```

108     else:
109         effect_sizes.append(0)
110
111 bars = ax_effect.bar(key_metrics_plot, effect_sizes, alpha=0.7, color='lightcoral')
112
113 ax_effect.axhline(y=0.2, color='green', linestyle='--', alpha=0.7, label='Small (0.2)')
114 ax_effect.axhline(y=0.5, color='orange', linestyle='--', alpha=0.7, label='Medium (0.5)')
115 ax_effect.axhline(y=0.8, color='red', linestyle='--', alpha=0.7, label='Large (0.8)')
116
117 for bar, effect_size in zip(bars, effect_sizes):
118     ax_effect.text(bar.get_x() + bar.get_width()/2, bar.get_height() + 0.01,
119                   f'{effect_size:.3f}', ha='center', va='bottom', fontweight='bold')
120
121 ax_effect.set_ylabel('Effect Size (|Cohen\'s d|)', fontsize=12)
122 ax_effect.set_title('Effect Sizes: Healthy Controls vs PTSD Patients', fontsize=14, pad=20)
123 ax_effect.set_xticklabels([m.upper() for m in key_metrics_plot], rotation=45)
124 ax_effect.legend()
125 ax_effect.grid(True, alpha=0.3)
126
127 plt.tight_layout()
128 plt.show()
129
130
131 summary_stats = []
132 key_metrics = ['mean_hr', 'sdnn', 'rmssd', 'pnn50', 'vlf_power', 'lf_power', 'hf_power', '
133               total_power', 'lf_hf_ratio', 'lf_log', 'hf_log', 'hf_norm', 'lf_norm', '
134               sd1', 'sd2', 'sd1_sd2_ratio', 'sample_entropy']
135
136 for metric in key_metrics:
137     healthy_mean = df[df['patient'] == 0][metric].mean()
138     ptsd_mean = df[df['patient'] == 1][metric].mean()
139
140     healthy_std = df[df['patient'] == 0][metric].std()
141     ptsd_std = df[df['patient'] == 1][metric].std()
142
143     summary_stats.append([
144         metric.upper(),
145         f'{healthy_mean:.2f}+/{healthy_std:.2f}' if not np.isnan(healthy_mean) else 'N/A',
146         f'{ptsd_mean:.2f}+/{ptsd_std:.2f}' if not np.isnan(ptsd_mean) else 'N/A'
147     ])
148
149 print("Summary Statistics:")
150 for metric, healthy, ptsd in summary_stats:
151     print(f"{metric}: Healthy Control = {healthy}, PTSD = {ptsd}")
152
153 p_values = []
154 for metric in key_metrics:
155     healthy_data = df[df['patient'] == 0][metric].dropna()
156     ptsd_data = df[df['patient'] == 1][metric].dropna()
157
158     if len(healthy_data) > 0 and len(ptsd_data) > 0:
159         u_stat, p_val = stats.mannwhitneyu(healthy_data, ptsd_data, alternative='two-sided')
160         p_values.append((metric, p_val))
161     else:
162         p_values.append((metric, np.nan))

```

```

162
163 print("\nP-Values for Each Metric (Mann-Whitney U test):")
164 for metric, p_val in p_values:
165     if np.isnan(p_val):
166         print(f"{metric}: N/A")
167     else:
168         print(f"{metric}: {p_val:.4f}")
169
170 print("\nEffect Sizes (Cohen's d) for Each Metric:")
171 for metric, p_val in p_values:
172     healthy_data = df[df['patient'] == 0][metric].dropna()
173     ptsd_data = df[df['patient'] == 1][metric].dropna()
174
175     if len(healthy_data) > 0 and len(ptsd_data) > 0:
176         d = cohens_d(healthy_data, ptsd_data)
177         print(f"{metric}: {d:.3f}")
178     else:
179         print(f"{metric}: N/A")
180
181
182 print(f"Total participants: {len(df)}")
183 print(f"Healthy controls: {len(df[df['patient'] == 0])}")
184 print(f"PTSD patients: {len(df[df['patient'] == 1])}")
185 print()

```

LISTING 4: HRV windowed analysis visualization: `hrv_windowed_analysis.ipynb`

```

1  import pandas as pd
2  import numpy as np
3  import matplotlib.pyplot as plt
4  import seaborn as sns
5  plt.rcParams['figure.dpi'] = 300
6  from scipy import stats
7  import warnings
8  warnings.filterwarnings('ignore')
9
10 df = pd.read_csv('hrv_windowed_results.csv')
11
12 df['tp_log'] = np.log(df['total_power'])
13
14 df_filtered = df[df['window_id'].isin([1])].copy()
15
16 patient_means = df_filtered.groupby(['name', 'patient']).agg({
17     'mean_hr': 'mean',
18     'sdnn': 'mean',
19     'rmssd': 'mean',
20     'pnn50': 'mean',
21     'vlf_power': 'mean',
22     'lf_power': 'mean',
23     'hf_power': 'mean',
24     'total_power': 'mean',
25     'tp_log': 'mean',
26     'lf_log': 'mean',
27     'hf_log': 'mean',
28     'lf_norm': 'mean',
29     'hf_norm': 'mean',
30     'lf_hf_ratio': 'mean',
31     'sd1': 'mean',
32     'sd2': 'mean',
33     'sd1_sd2_ratio': 'mean',
34     'sample_entropy': 'mean'
35 }).reset_index()
36
37 patient_means['group'] = patient_means['patient'].map({0: 'Healthy Control', 1: 'PTSD'})
38
39 plt.style.use('default')
40 group_colors = {'Healthy Control': '#5EBB86', 'PTSD': '#3267C3'}
41 palette = [group_colors['Healthy Control'], group_colors['PTSD']]
42
43 fig = plt.figure(figsize=(20, 25), dpi=300)
44
45
46 time_domain_metrics = ['mean_hr', 'sdnn', 'rmssd', 'pnn50']
47 frequency_domain_metrics = ['vlf_power', 'lf_power', 'hf_power', 'total_power', 'lf_hf_ratio',
48     'lf_log', 'hf_log', 'tp_log']
49 nonlinear_metrics = ['sd1', 'sd2', 'sd1_sd2_ratio', 'sample_entropy']
50
51 metric_labels = {
52     'mean_hr': 'Mean Heart Rate (bpm)',
53     'sdnn': 'SDNN (ms)',
54     'rmssd': 'RMSSD (ms)',

```

```

54     'pnn50': 'pNNS50 (%)',
55     'vlf_power': 'VLF Power (ms2)',
56     'lf_power': 'LF Power (ms2)',
57     'hf_power': 'HF Power (ms2)',
58     'total_power': 'Total Power (ms2)',
59     'lf_hf_ratio': 'LF/HF Ratio',
60     'lf_log': 'LF Power (log)',
61     'hf_log': 'HF Power (log)',
62     'tp_log': 'Total Power (log ms2)',
63     'lf_norm': 'LF Power (n.u.)',
64     'hf_norm': 'HF Power (n.u.)',
65     'sd1': 'SD1 (ms)',
66     'sd2': 'SD2 (ms)',
67     'sd1_sd2_ratio': 'SD1/SD2 Ratio',
68     'sample_entropy': 'Sample Entropy'
69 }
70
71 for i, metric in enumerate(time_domain_metrics, 1):
72     ax = plt.subplot(4, 4, i)
73
74     sns.boxplot(data=patient_means, x='group', y=metric, ax=ax, palette=palette)
75
76     means = patient_means.groupby('group')[metric].mean()
77     for j, (group, mean_val) in enumerate(means.items()):
78         ax.scatter(j, mean_val, marker='D', s=50, color='red', zorder=10, label='Mean' if j ==
79                     0 else "")
80
81     healthy = patient_means[patient_means['patient'] == 0][metric].dropna()
82     ptsd = patient_means[patient_means['patient'] == 1][metric].dropna()
83
84     if len(healthy) > 0 and len(ptsd) > 0:
85         u_stat, p_val = stats.mannwhitneyu(healthy, ptsd, alternative='two-sided')
86         ax.set_title(f'{metric.upper()}\np-value: {p_val:.4f}')
87     else:
88         ax.set_title(f'{metric.upper()}')
89
90     ax.set_ylabel(metric_labels.get(metric, metric.upper()))
91     ax.set_xlabel('')
92
93 for i, metric in enumerate(frequency_domain_metrics, 5):
94     ax = plt.subplot(4, 4, i)
95
96     df_plot = patient_means.copy()
97
98     sns.boxplot(data=df_plot, x='group', y=metric, ax=ax, palette=palette)
99
100    means = df_plot.groupby('group')[metric].mean()
101    for j, (group, mean_val) in enumerate(means.items()):
102        ax.scatter(j, mean_val, marker='D', s=50, color='red', zorder=10, label='Mean' if j ==
103                    0 else "")
104
105    healthy = df_plot[df_plot['patient'] == 0][metric].dropna()
106    ptsd = df_plot[df_plot['patient'] == 1][metric].dropna()
107
108    if len(healthy) > 0 and len(ptsd) > 0:

```

```

107     u_stat, p_val = stats.mannwhitneyu(healthy, ptsd, alternative='two-sided')
108     ax.set_title(f'{metric.upper()}\np-value: {p_val:.4f}')
109     else:
110         ax.set_title(f'{metric.upper()}')
111
112     ax.set_ylabel(metric_labels.get(metric, metric.upper()))
113     ax.set_xlabel('')
114
115 for i, metric in enumerate(nonlinear_metrics, 13):
116     ax = plt.subplot(4, 4, i)
117
118     sns.boxplot(data=patient_means, x='group', y=metric, ax=ax, palette=palette)
119
120     means = patient_means.groupby('group')[metric].mean()
121     for j, (group, mean_val) in enumerate(means.items()):
122         ax.scatter(j, mean_val, marker='D', s=50, color='red', zorder=10, label='Mean' if j ==
123             0 else "")
124
125     healthy = patient_means[patient_means['patient'] == 0][metric].dropna()
126     ptsd = patient_means[patient_means['patient'] == 1][metric].dropna()
127
128     if len(healthy) > 0 and len(ptsd) > 0:
129         u_stat, p_val = stats.mannwhitneyu(healthy, ptsd, alternative='two-sided')
130         ax.set_title(f'{metric.upper()}\np-value: {p_val:.4f}')
131     else:
132         ax.set_title(f'{metric.upper()}')
133
134     ax.set_ylabel(metric_labels.get(metric, metric.upper()))
135     ax.set_xlabel('')
136
137 healthy_count = len(patient_means[patient_means['patient'] == 0])
138 ptsd_count = len(patient_means[patient_means['patient'] == 1])
139
140
141 plt.tight_layout(rect=[0, 0.03, 1, 0.93])
142 plt.suptitle('HRV of First Window (2 min)', fontsize=18, y=0.95, fontweight='bold')
143 plt.show()
144
145
146 fig_corr = plt.figure(figsize=(12, 10), dpi=300)
147 ax_corr = plt.subplot(1, 1, 1)
148
149 healthy_data = patient_means[patient_means['patient'] == 0]
150 hrv_metrics = ['mean_hr', 'sdnn', 'rmssd', 'pnn50', 'hf_power', 'lf_power', 'total_power', '
151     lf_hf_ratio', 'sd1', 'sd2', 'sd1_sd2_ratio', 'sample_entropy']
152
153 corr_matrix = healthy_data[hrv_metrics].corr()
154
155 sns.heatmap(corr_matrix, annot=True, cmap='coolwarm', center=0, ax=ax_corr, fmt='.2f',
156     cbar_kws={'shrink': 0.8}, square=True, linewidths=0.5)
157 ax_corr.set_title('HRV Metrics Correlation Matrix - Healthy Controls', fontsize=16, fontweight=
158     'bold', pad=20)
159 ax_corr.set_xticklabels(ax_corr.get_xticklabels(), rotation=45, ha='right')

```

```

159 ax_corr.set_yticklabels(ax_corr.get_yticklabels(), rotation=0)
160
161 plt.tight_layout()
162 plt.show()
163
164 fig_effect = plt.figure(figsize=(10, 6), dpi=300)
165 ax_effect = plt.subplot(1, 1, 1)
166
167 key_metrics_plot = ['mean_hr', 'sdnn', 'rmssd', 'pnn50',
168                    'vlf_power', 'lf_power', 'hf_power', 'total_power', 'lf_hf_ratio', 'lf_log'
169                    , 'hf_log', 'hf_norm', 'lf_norm',
170                    'sd1', 'sd2', 'sd1_sd2_ratio', 'sample_entropy']
171
172 def cohens_d(group1, group2):
173     n1, n2 = len(group1), len(group2)
174     pooled_std = np.sqrt(((n1 - 1) * group1.var() + (n2 - 1) * group2.var()) / (n1 + n2 - 2))
175     d = (group1.mean() - group2.mean()) / pooled_std
176     return d
177
178 effect_sizes = []
179 for metric in key_metrics_plot:
180     healthy = patient_means[patient_means['patient'] == 0][metric].dropna()
181     ptsd = patient_means[patient_means['patient'] == 1][metric].dropna()
182
183     if len(healthy) > 0 and len(ptsd) > 0:
184         d = cohens_d(healthy, ptsd)
185         effect_sizes.append(abs(d))
186     else:
187         effect_sizes.append(0)
188
189 bars = ax_effect.bar(key_metrics_plot, effect_sizes, alpha=0.7, color='lightcoral')
190
191 ax_effect.axhline(y=0.2, color='green', linestyle='--', alpha=0.7, label='Small (0.2)')
192 ax_effect.axhline(y=0.5, color='orange', linestyle='--', alpha=0.7, label='Medium (0.5)')
193 ax_effect.axhline(y=0.8, color='red', linestyle='--', alpha=0.7, label='Large (0.8)')
194
195 for bar, effect_size in zip(bars, effect_sizes):
196     ax_effect.text(bar.get_x() + bar.get_width()/2, bar.get_height() + 0.01,
197                   f'{effect_size:.3f}', ha='center', va='bottom', fontweight='bold')
198
199 ax_effect.set_ylabel('Effect Size (|Cohen\'s d|)', fontsize=12)
200 ax_effect.set_title('Effect Sizes: Healthy Controls vs PTSD Patients', fontsize=14, pad=20)
201 ax_effect.set_xticklabels([m.upper() for m in key_metrics_plot], rotation=45)
202 ax_effect.legend()
203 ax_effect.grid(True, alpha=0.3)
204
205 plt.tight_layout()
206 plt.show()
207
208 summary_stats = []
209 key_metrics = ['mean_hr', 'sdnn', 'rmssd', 'pnn50', 'hf_power', 'lf_power', 'total_power', '
210               lf_hf_ratio', 'sd1', 'sd2', 'sd1_sd2_ratio', 'sample_entropy']
211 for metric in key_metrics:

```

```

212 healthy_mean = patient_means[patient_means['patient'] == 0][metric].mean()
213 ptsd_mean = patient_means[patient_means['patient'] == 1][metric].mean()
214
215 healthy_std = patient_means[patient_means['patient'] == 0][metric].std()
216 ptsd_std = patient_means[patient_means['patient'] == 1][metric].std()
217
218 summary_stats.append([
219     metric.upper(),
220     f'{healthy_mean:.2f}+/-{healthy_std:.2f}' if not np.isnan(healthy_mean) else 'N/A',
221     f'{ptsd_mean:.2f}+/-{ptsd_std:.2f}' if not np.isnan(ptsd_mean) else 'N/A'
222 ])
223
224 p_values = []
225 effect_sizes_summary = []
226 for metric in key_metrics:
227     healthy_data = patient_means[patient_means['patient'] == 0][metric].dropna()
228     ptsd_data = patient_means[patient_means['patient'] == 1][metric].dropna()
229
230     if len(healthy_data) > 0 and len(ptsd_data) > 0:
231         u_stat, p_val = stats.mannwhitneyu(healthy_data, ptsd_data, alternative='two-sided')
232         d = cohens_d(healthy_data, ptsd_data)
233         p_values.append((metric, p_val))
234         effect_sizes_summary.append((metric, d))
235     else:
236         p_values.append((metric, np.nan))
237         effect_sizes_summary.append((metric, np.nan))
238
239 print("\nP-Values for Each Metric (Mann-Whitney U test):")
240 for metric, p_val in p_values:
241     if np.isnan(p_val):
242         print(f"{metric}: N/A")
243     else:
244         print(f"{metric}: {p_val:.4f}")
245
246 print("\nEffect Sizes (Cohen's d) for Each Metric:")
247 for metric, d in effect_sizes_summary:
248     if np.isnan(d):
249         print(f"{metric}: N/A")
250     else:
251         print(f"{metric}: {d:.3f}")
252
253
254 fig_progression = plt.figure(figsize=(15, 10), dpi=300)
255
256 df_progression = df[df['window_id'].isin([1, 2, 3, 4, 5, 6])].copy()
257 df_progression['group'] = df_progression['patient'].map({0: 'Healthy Control', 1: 'PTSD'})
258
259 progression_metrics = ['sdnn', 'rmssd', 'pnn50', 'lf_hf_ratio', 'lf_log', 'hf_log']
260 metric_labels = ['sdnn (ms)', 'rmssd (ms)', 'pnn50', 'lf_hf_ratio', 'lf_log', 'hf_log']
261
262 for i, (metric, ylabel) in enumerate(zip(progression_metrics, metric_labels), 1):
263     ax = plt.subplot(3, 3, i)
264
265     for group in ['Healthy Control', 'PTSD']:
266         group_data = df_progression[df_progression['group'] == group]

```

```

267     if len(group_data) > 0:
268         metric_by_window = group_data.groupby('window_id')[metric].mean()
269         std_metric_by_window = group_data.groupby('window_id')[metric].std()
270
271         ax.errorbar(metric_by_window.index, metric_by_window.values,
272                     yerr=std_metric_by_window.values, label=group, marker='o',
273                     capsize=5, linewidth=2, markersize=6)
274
275     ax.set_xlabel('Window ID')
276     ax.set_ylabel(ylabel)
277     ax.set_title(f'{metric.upper()} Progression')
278     ax.legend()
279     ax.grid(True, alpha=0.3)
280     ax.set_xticks([1, 2, 3, 4, 5, 6])
281
282
283 fig_progression.suptitle('HRV Metric Progression Across Time Windows', fontsize=16, y=0.98)
284
285 plt.tight_layout(rect=[0, 0.03, 1, 0.95])
286 plt.show()

```

LISTING 5: HRV analysis for valence changes: `hrv_valence_analysis.ipynb`

```

1 import pandas as pd
2 import numpy as np
3 from scipy import stats
4 import matplotlib.pyplot as plt
5 plt.rcParams['figure.dpi'] = 300
6 import seaborn as sns
7
8 df_baseline = pd.read_csv('hrv_overall_results_base.csv')
9 df_neg = pd.read_csv('hrv_overall_results_neg.csv')
10
11 df_baseline['group'] = df_baseline['patient'].map({0: 'Healthy Control', 1: 'PTSD Patient'})
12 df_neg['group'] = df_neg['patient'].map({0: 'Healthy Control', 1: 'PTSD Patient'})
13
14 df_merged = pd.merge(df_baseline, df_neg, on=['name', 'patient', 'group'], suffixes=('_baseline', '_neg'))
15
16 hrv_metrics = ['mean_hr', 'sdnn', 'rmssd', 'pnn50', 'vlf_power', 'lf_power', 'hf_power', 'lf_log', 'hf_log',
17               'total_power', 'lf_hf_ratio', 'sd1', 'sd2', 'sd1_sd2_ratio']
18
19 for metric in hrv_metrics:
20     df_merged[f'{metric}_diff'] = df_merged[f'{metric}_neg'] - df_merged[f'{metric}_baseline']
21
22 results = []
23 difference_metrics = [f'{metric}_diff' for metric in hrv_metrics]
24
25 print("HRV Change Analysis: Baseline to Negative Condition")
26 print("=" * 60)
27 print(f"{'Metric':<20} {'Healthy Control Mean +/- SD':<20} {'PTSD Mean +/- SD':<20} {'p-value':<10} {'Effect Size':<10}")
28 print("-" * 80)
29
30 for i, metric in enumerate(hrv_metrics):
31     diff_metric = f'{metric}_diff'
32
33     ctrl_data = df_merged[df_merged['patient'] == 0][diff_metric].dropna()
34     ptsd_data = df_merged[df_merged['patient'] == 1][diff_metric].dropna()
35
36     if len(ctrl_data) > 0 and len(ptsd_data) > 0:
37         ctrl_mean = ctrl_data.mean()
38         ctrl_std = ctrl_data.std()
39         ptsd_mean = ptsd_data.mean()
40         ptsd_std = ptsd_data.std()
41
42         # Mann-Whitney U test for between-group comparison
43         u_stat, p_val = stats.mannwhitneyu(ctrl_data, ptsd_data, alternative='two-sided')
44
45         # Wilcoxon Signed-Rank tests for within-group changes
46         ctrl_wilcoxon_stat, ctrl_p_val = stats.wilcoxon(ctrl_data, alternative='two-sided')
47         ptsd_wilcoxon_stat, ptsd_p_val = stats.wilcoxon(ptsd_data, alternative='two-sided')
48
49         pooled_std = np.sqrt(((len(ctrl_data) - 1) * ctrl_std**2 + (len(ptsd_data) - 1) * ptsd_std**2) /
50                               (len(ctrl_data) + len(ptsd_data) - 2))

```

```

51     cohens_d = (ctrl_mean - ptsd_mean) / pooled_std if pooled_std != 0 else 0
52
53     results.append({
54         'metric': metric,
55         'ctrl_mean': ctrl_mean,
56         'ctrl_std': ctrl_std,
57         'ptsd_mean': ptsd_mean,
58         'ptsd_std': ptsd_std,
59         'p_value': p_val,
60         'ctrl_wilcoxon_p': ctrl_p_val,
61         'ptsd_wilcoxon_p': ptsd_p_val,
62         'effect_size': abs(cohens_d),
63         'cohens_d': cohens_d
64     })
65
66     print(f"{metric.upper():<20} {ctrl_mean:+.2f}/{-ctrl_std:.2f}{'':>7} {ptsd_mean:+.2f}
67         {+/-ptsd_std:.2f}{'':>7} {p_val:.4f}{'':>6} {abs(cohens_d):.3f}")
68
69 fig, axes = plt.subplots(4, 4, figsize=(20, 25), dpi=300)
70 axes = axes.flatten()
71
72 group_colors = {'Healthy Control': "#5EBB86", 'PTSD Patient': "#3267C3"}
73 palette = [group_colors['Healthy Control'], group_colors['PTSD Patient']]
74
75 for i, metric in enumerate(hrv_metrics):
76     if i < len(axes):
77         ax = axes[i]
78         diff_metric = f'{metric}_diff'
79
80         sns.boxplot(data=df_merged, x='group', y=diff_metric, hue='group', ax=ax, palette=
81             palette, legend=False)
82
83         means = df_merged.groupby('group')[diff_metric].mean()
84         for j, (group, mean_val) in enumerate(means.items()):
85             ax.scatter(j, mean_val, marker='D', s=50, color='red', zorder=10)
86
87         ax.axhline(y=0, color='black', linestyle='--', alpha=0.5)
88
89         result = next((r for r in results if r['metric'] == metric), None)
90         p_val = result['p_value'] if result else np.nan
91
92         ax.set_title(f'{metric.upper()}\np={p_val:.4f}', fontsize=10)
93         ax.set_ylabel(f'Change in {metric}')
94         ax.set_xlabel('')
95
96 for i in range(len(hrv_metrics), len(axes)):
97     axes[i].remove()
98
99 plt.tight_layout(rect=[0, 0.03, 1, 0.96])
100 plt.suptitle('HRV Changes from Baseline to Negative Valence (Neg-Base) by Group ',
101             fontsize=16, fontweight='bold', y=0.98)
102 plt.show()
103

```

```

104 print(f"\nSample sizes:")
105 print(f"Healthy Controls: {len(df_merged[df_merged['patient'] == 0])}")
106 print(f"PTSD Patients: {len(df_merged[df_merged['patient'] == 1])}")
107
108 print(f"\nWithin-group changes (Wilcoxon Signed-Rank):")
109 print("=" * 50)
110 print("Healthy Controls - significant changes from baseline:")
111 ctrl_sig = [r for r in results if r['ctrl_wilcoxon_p'] < 0.05]
112 if ctrl_sig:
113     for result in ctrl_sig:
114         direction = "increased" if result['ctrl_mean'] > 0 else "decreased"
115         print(f"- {result['metric'].upper()}: {direction} (p={result['ctrl_wilcoxon_p']:.4f})")
116 else:
117     print("No significant changes found.")
118
119 print("\nPTSD Patients - significant changes from baseline:")
120 ptsd_sig = [r for r in results if r['ptsd_wilcoxon_p'] < 0.05]
121 if ptsd_sig:
122     for result in ptsd_sig:
123         direction = "increased" if result['ptsd_mean'] > 0 else "decreased"
124         print(f"- {result['metric'].upper()}: {direction} (p={result['ptsd_wilcoxon_p']:.4f})")
125 else:
126     print("No significant changes found.")
127
128 print(f"\nBetween-group differences (Mann-Whitney U):")
129 print("=" * 50)
130 sig_results = [r for r in results if r['p_value'] < 0.05]
131 if sig_results:
132     for result in sig_results:
133         direction = "increased" if result['cohens_d'] > 0 else "decreased"
134         print(f"- {result['metric'].upper()}: PTSD group {direction} more than control (p={
            result['p_value']:.4f}, d={result['cohens_d']:.3f})")
135 else:
136     print("No significant differences found.")

```