

Quantifying neurophysiological mechanism through heart rate variability: the case of cognitive stress

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Abstract

In the modern contemporary world, our life has become a warehouse of stress, consisting more of mental stress than physical stress. It can be shown that prolonged mental stress can lead to serious dysfunctionality in the autonomous nervous system (ANS), which, in turn, is reflected in heart rate variability (HRV). In this study, we have discussed the effectiveness of different metrics obtained from the analysis of HRV signals. The HRV analyses are being conducted in majorly three domains by the research community, namely, time, frequency, and non-linear. We have compiled metrics for all the three techniques and compared their effectiveness. To assess the effect of cognitive stress, a comparative study is typically developed where two sets of HRV data are procured from the same subject, one in a completely healthy and stressless condition and the other under a simulated, controlled cognitive stress. Many of the datasets are pretty comprehensive, having a vast number of subjects and the analysis comprising up to 22 different parameters. A comparative study of these datasets revealed a significant drop in HRV during stress when analyzed in time and non-linear domains. On the other hand, a substantial increase in HRV is spotted when measured with the help of high-to-low-frequency methodology. Overall, the non-linear metrics were found to be more robust and gave more consistent results than the time or frequency domain metrics.

Keywords

heart rate variability, autonomous nervous system, cognitive task, mental stress, ECG signal processing, non-linear metrics

1. Introduction

Prolonged exposure to daily stress results in a continuous and destructive effect on the human mind. Cognitive dysfunctions and depressions are the various effects of the stress, which may also lead to death (Saxena et al., 2002). It has been reported that 50% of the employees in the world face several work-related stresses that lead to depression as well (Engin, 2004). Several studies show that prolonged exposure to stress may lead to decreased quality of life and acquired acute depression, which affect mental health (Arzeno et al., 2006; Israel et al., 2005).

Nowadays, individuals are experiencing significantly more mental anxieties than in the past. While various reasons contribute to the current state, the fundamental driver would be the inaccessibility of unwinding time and the consistent need for difficult mental work. Cognitive tasks, which are relatively harder, cause frustration due to underestimation of their time of completion, which ultimately results in anxiety and stress (Badre, 2021). Persistent stress is a significant contributor to morbidity and mortality (Dossett et al., 2020).

In this study, we will be focusing on the effect of cognitive stress on the autonomous nervous system

(ANS). The ANS helps us in realizing instantaneous motor functions based on external stimuli (Israel et al., 2005; Saxena et al., 2002). Thus, it will be considered an essential factor to measure acute stress in a non-invasive way, which is known to be fundamental and reliable for measuring the activity of ANS (Bansal et al., 2007). Control of this activity is done by sympathetic and parasympathetic responses of ANS and can be determined by the responses of heart rate variability (HRV) signals (Dobbs et al., 1984). HRV can be used to measure the mental anxiety of normal healthy individuals by comparing them at rest and at stressful conditions. It was reported that even a subtle change in cognitive activity can be detected through HRV (Choi, 2017); no wonder HRV is regarded as a clinical index for assessing psychophysiological resilience (Mourtakos et al., 2021).

II. The neurophysiological mechanism behind HRV

The sinoatrial node (SA node) refers to a bundle of specialized cells in the heart responsible for initiating heartbeats. HRV refers to the alterations of the time

intervals between subsequent heartbeats. The variations are the result of different complex physiological functions. Heart–brain interaction and autonomic nervous system dynamics are probably the most dominating physiological function behind HRV. The heart–brain connection pathways are explained in Figure 1.

There are two sets of nerves, sympathetic and parasympathetic (vagus), which, in combination, maintain the equilibrium of the heart rate (HR) by slowing down or speeding up the rate, respectively. During routine tasks, rest, or sleep, HR is lower than the intrinsic rate, and parasympathetic activity predominates. When a stressful situation emerges, characterized by an HR >100 bpm, sympathetic activity takes over.

The descending sympathetic nerve targets the SA node via the underlying cardiac nervous system and much of the myocardium. Action potentials conducted by these motor neurons trigger the release of noradrenaline and adrenaline, increasing HR and enhancing atrial and ventricular contractility. After the onset of sympathetic stimulation, there is a delay of up to 5 s before the heart rate gradually increases with

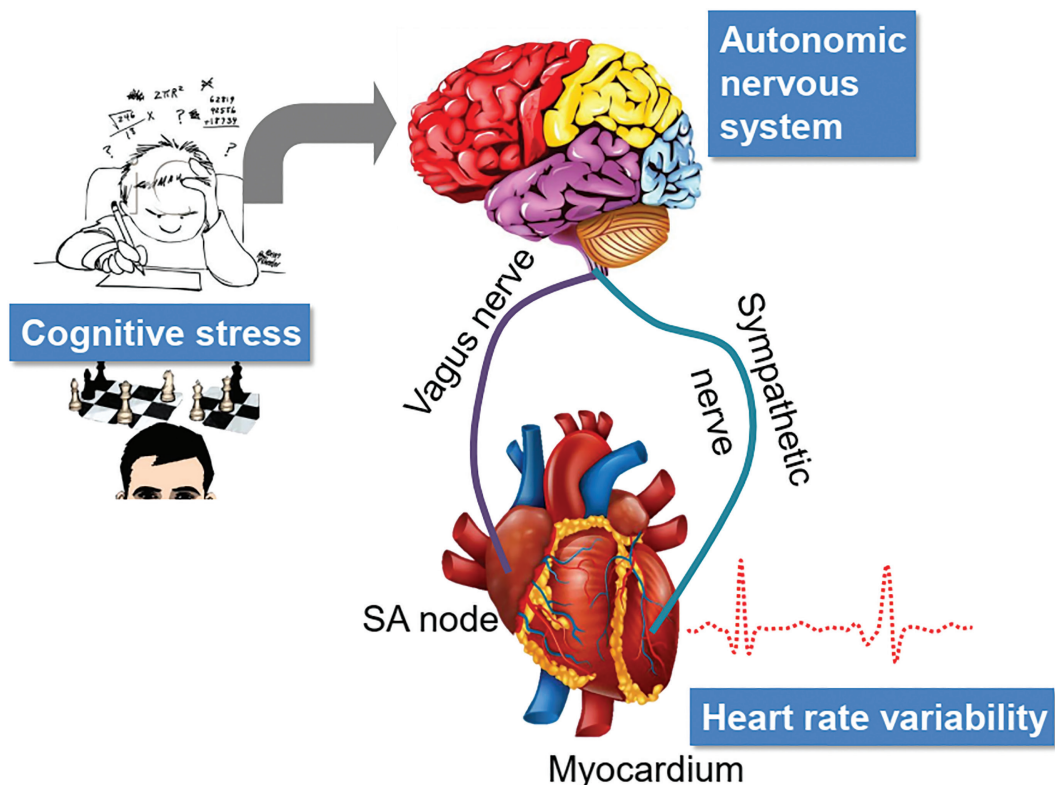


Figure 1: Neurophysiological mechanism of HRV under cognitive stress. HRV, heart rate variability.

stimulation, reaching a steady level within 20–30 s of continuous stimulation. Even brief sympathetic stimulation can affect HR rate and HRV rhythm for 5–10 s. The relatively slow response to sympathetic stimulation contrasts with near-instantaneous vagal stimulation. Therefore, an increase or decrease in heart rate, or an abrupt change between heart rates, is mediated primarily by parasympathetic nerves.

Although the sympathetic nervous system (SNS) is dominant during stress, including cognitive one, there is yet another emerging perspective, especially when the stress is related to a cognitive task. This is the vagal reactivity and the recuperation measures that have been connected to intellectual execution (Capuana et al., 2014). Vagal reactivity addresses the change among standards and a particular occasion, such as finishing an undertaking, and it is fundamental to chronicle it to assess the person's flexibility to the circumstance (Laborde et al., 2018). Recuperation is typically seen as a cycle of rebuilding; it alludes to the change between the occasion and a period point after the occasion when the vagal action must be like the pattern. Equivalent to vagal reactivity, vagal recuperation assumes a significant part in the versatility of the creature (Sinha et al., 2015). These two perspectives are ineffectively investigated with intellectual working. In any case, as indicated by the vagal tank hypothesis (Laborde et al., 2018), considering the vagal action and the vagal recuperation during various psychological assignments could be intriguing. This kind of study could permit to see

better what heart vagal control means for a few key self-administrative parts of conduct (Delmastro et al., 2020; Engert et al., 2017; Ghiasi et al., 2020; Holzman & Bridgett, 2017; Ishaque et al., 2021; Pykett et al., 2020; Rachakonda et al., 2020; Rudovic et al., 2018). Furthermore, the study is indicative of the evident contrasts between benchmark, task execution, and recuperation, which are identified with psychological debilitation (Betti et al., 2018; Capdevila et al., 2021; Chen et al., 2020; Hong et al., 2020; Koren et al., 2020; Masood & Alghamdi, 2019; Ni et al., 2021; Saini & Gupta, 2019; Wu et al., 2019).

III. Analysis of HRV

a. HRV extraction from ECG

In the medical domain, ECG signals have various applications like monitoring different types of human diseases that are directly or indirectly related with the function of human heart (Brüser et al., 2015; Cox et al., 1968; Jatmiko et al., 2019; Kang et al., 2016; Lassoued et al., 2018; Lee, 2016; Mporas et al., 2015; Pope et al., 2000). Among them, HRV analysis is one of the key tools for measuring the heart condition at the time of human stress. Figure 2 represents different parameters of ECG signal like RR interval, QT interval, PR interval, ST segment, PR segment, QRS complex, etc. (He et al., 2017; Lastre-Domínguez et al., 2018; Ye et al., 2012). Alongside with that, different statistical analyzing tools are also used to extrapolate the

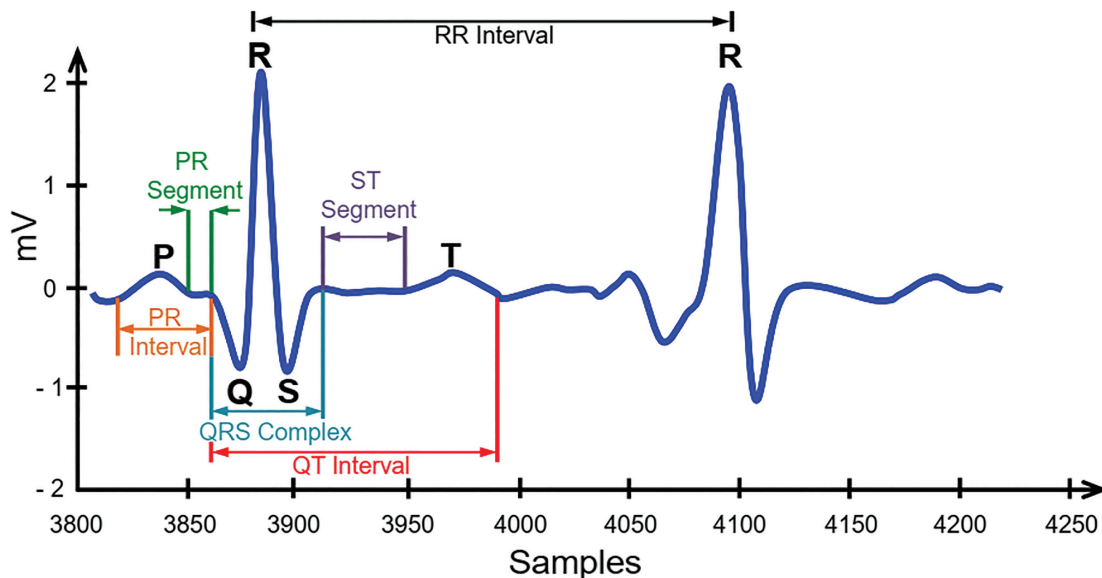


Figure 2: Usual cardiac cycle (heartbeat) from MIT-BIH arrhythmia database (ECG 100 recordings).

determining factors of stress from the acquired HRV signals (Afonso, 1993; Arzeno et al., 2006; Dobbs et al., 1984).

Frequency- and time-domain measures of HRV are accumulated as stated by the principles depicted by European Society of Cardiology and the North American Society of Pacing and Electrophysiology (Malik et al., 1996).

b. Time-domain analysis

Moderate prediction of HRV signals can be followed by means of RR intervals of the signals. For short-term analysis, standard derivation of the ECG signals was taken for 5 min for stress and non-stress conditions, and segmental analysis of signals is done to compare the abnormality of the signals in the stressed condition, which is also known as QRS complex segmentation of RR intervals (Alhussainy, 2020; Malik et al., 1996). Now for the long-term analysis, RR intervals are investigated for about 24 hr. The comparison between the signals at rest and at stress is measured to find scalar difference between those intervals. Analyses of such signals provide us with a methodology that will be effective in flawlessly determining the condition of mental stress in subjects. The simplest variance of this signal is used to compute the square root of the variance and the standard deviation of NN (or RR) intervals.

On the other hand, physiological states also affect the variation of HRV. Such essence can be reproduced, manipulated, and analyzed by determining the magnitude and duration of QRS intervals. Thus, the accuracy of the QRS intervals is necessary for the psychological states of RR intervals, and different types of statistical manipulation have been done to define such intervals (Adler et al., 2007). Critical distortion can be caused if the sampling frequency is <500 Hz, especially when spectrum estimation is done (Merri et al., 1990). In the case of a normal day activity, sympathetic and parasympathetic variations fluctuate drastically (Goldberger, 1999). The locations of the QRS complex for some small absolute values are usually noisy (Al-Hazimi et al., 2002) and necessitate sophisticated algorithms for the QRS signal detection (Balda et al., 1977). Noise performance of such algorithms can be evaluated by a method proposed by Friesen et al. (1990). The derivative-based algorithm is conceptualized by Ahlstrom and Tompkins (1985), while, an algorithm for the QRS signals was formulated by Pan and Tompkins (1985) to incorporate noisy condition in the accumulated data. The ECG signals and the QRS complexes are widely

distinguished using differentiation method. High slopes of derivation give a clear contrast between QRS and other ECG waves. In non-linear transformation, this is done by squaring signal samples to achieve positivity before integration. Higher frequency distinguishing techniques are meant to determine QRS complex and have been applied by Daskalov and Christov (1999). The key to detect thresholds by adoptive amplitude levels is to pass the signal through a band-pass filter that will implicate the new peak noise of the system.

c. Frequency-domain analysis

Apart from time-domain analysis, frequency-domain analysis (i.e., measuring the intervals in high frequency as well as in low frequency) can be done by micro-processor-equipped technology. The advantage of using frequency-domain analysis over time-domain is that HRV signal spectrum analysis is done in frequency-domain analysis. An additional harmonic shows irregular time sampled in the frequency domain in the spectrum. This frequency ranges between 0.17 Hz and 0.5 Hz, and this is a phenomenon that happens due to the respiration of vagus and sympathetic nerves (Malik et al., 1996). Autoregressive (AR) nodal-based fast Fourier transform (FFT) is used to determine power spectral density (PSD). A huge array of frequencies can be determined by this method of PSD, while AR methods are assigned to divide spectrums into components (Niskanen et al., 2004).

The spectrum analyses of the HRV measures are done on the basis of two frequency bands, where the frequency ranging between 0.04 Hz and 0.17 Hz is called a low-frequency band (LowF), where the other spectrum ranges within the high-frequency band (HighF) varying from 0.15 Hz to 0.4 Hz. Such measures are either normalized (and having no units) or are denoted with unit ms^2 . The non-conventional approach of this study demands the presentation of the report in a unique way. Thus, the normalized unit approach is validated in this study. The advantages of using such a non-conventional way are that the measures can be kept out from pooling and the acquired data can be transfigured into a quantity having a unit of ms^2 , whenever needed (Aditya Pramanta et al., 2016; Choi & Gutierrez-Osuna, 2011; De Nadai et al., 2016; He et al., 2019; Lackner et al., 2011; Papousek et al., 2010; Soekadar et al., 2016; Traina et al., 2011).

The measures can also be done in ms^2/Hz , which has been mentioned in a single study (Schubert et al., 2009). As this is for the sake of informality and normalization, these data have been considered irrelevant

and thus excluded from the study. Other reports (Marques et al., 2010) also show frequency-domain features that are log transformed to either low frequency (LF log) or high frequency (HF log). A typical transformation for LowF is, $\text{Mean [low frequency]} (\text{ms}^2) = \exp(\text{Mean}(\text{LF log}))$ and standard deviation [low frequency] (ms^2) = $\text{Stdd}(\text{LF log}) \times [\exp(\text{Mean}(\text{LF log}))]^2$, to calculate the Mean and standard deviation (Stdd), respectively.

d. Statistical data handling

The methodology that has been used for the analysis of HRV signals is quite standard for doing systematic reviews. The significance of the p -values will be considered if those measures are <0.05 , which is also related to 95% confidence interval (CI) differences. Open-source meta-analysis software is used for statistical computations. In many cases, similar data pools have been created to eliminate the repetitive HRV signals. In several papers, the mean difference method is applied to get through such pools (Billman et al., 2015; Brouwer et al., 2015; Fukunishi et al., 2018; Kontaxis et al., 2018; Lombardi & Stein, 2011; Ribeiro & Cunha, 2018; Sutton et al., 2000). As a result, we got 98.89% of CI.

Q-statistics tests are performed for arbitrary heterogeneity and fixed effect models. Indication of effect

sites in the whole study can be observed by this approach. To accompany the Q-statistic approach, we have also taken the indicative strategy. This helps us in indexing the degree of heterogeneity across the vastness of the study. Although it might look like a sampling error, this strategy is effective because its reliability lies in the total variability of effect sizes due to the variability between two different studies (Chalmers et al., 2014). The I^2 variability has predefined indicative measures to determine the subnormal ($I^2 = 25$ or 25%), normal ($I^2 = 50$ or 50%), and abnormal ($I^2 = 75$ or 75%) heterogeneity.

e. Types of analysis

The three major modes of HRV analysis are shown in Figure 3 in a combined fashion, whereas, the tendency of HRV signals in the rest and in the stressed states are depicted in Tables 1, 2, and 4, for time, frequency, and non-linear techniques, respectively (Acharya et al., 2006; Behzadi et al., 2007; Bhattacharyya & Lowe, 2004; Zandbelt et al., 2008). Information like the quality of subjects assigned to each and individual study has been placed in these tables (Tables 1, 2, and 4) chronologically. All these data are acquired and tabulated by the process of pooling (Akay, 2012; Akselrod et al., 1981; Cropanzano et al., 2017; Elfenbein, 2017; Gabella,

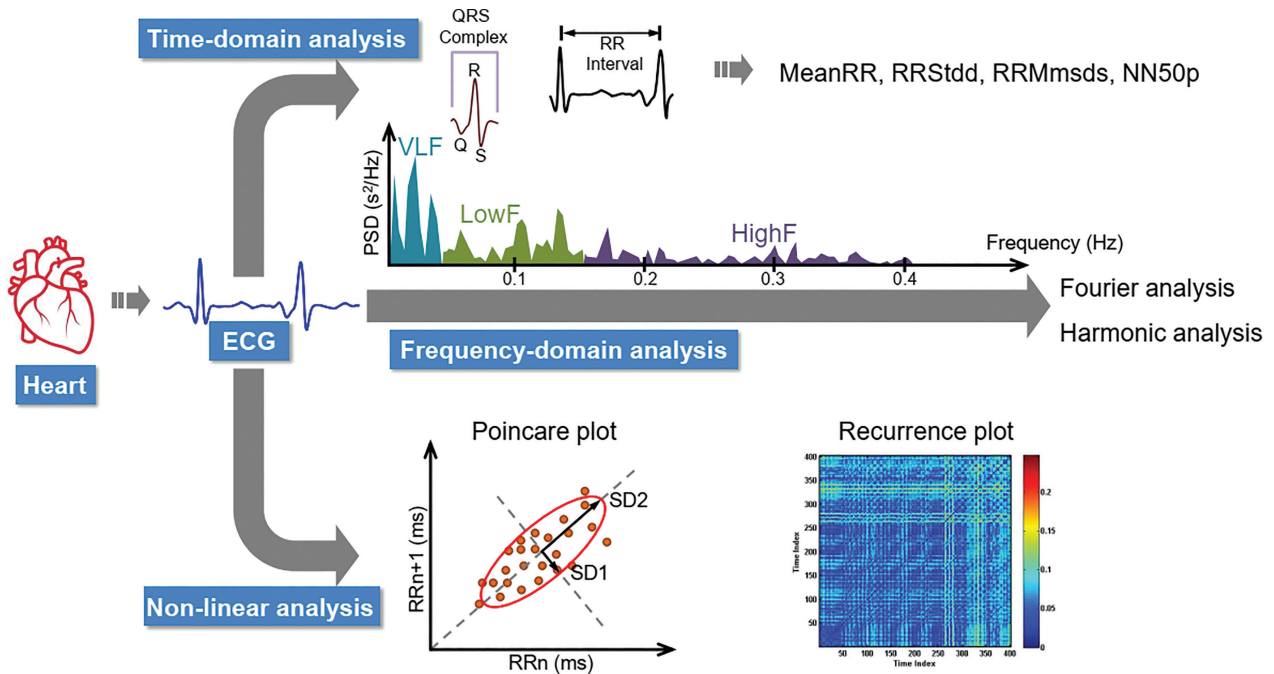


Figure 3: Signal collection and HRV analysis in three different domains (time, frequency, and non-linear). HRV, heart rate variability.

Table 1: The metrics considered in the time domain and their values under stress and rest conditions

Metric	References	Meta analysis report		Stress		Rest	
		Mean %-tile	Characteristics	Mean	Stdd	Mean	Stdd
MeanRR	Vuksanović (2007)	0.0033	Low	740.74	263.25	806.59	249.54
	Tharion et al. (2009)	0.0117	Very low	777.49	114.38	867.36	114.12
	Schubert et al. (2009)	0.0183	Low	686.47	240.82	808.67	206.25
	Papousek et al. (2010)	0.0926	Very low	617.92	210.44	819.73	244.14
	Lackner et al. (2011)	0.1287	Low	765.93	314.33	837.15	324.60
	Taelman et al. (2011)	0.1997	Very low	755.44	134.52	863.54	147.12
RRStdd	Tharion et al. (2009)	0.0894	Very low	52.42	21.51	74.32	25.21
	Schubert et al. (2009)	0.0352	Very high	96.25	86.38	33.54	23.44
	Taelman et al. (2011)	0.0376	Very low	35.27	16.22	46.38	19.49
	Visnovcova et al. (2014)	0.5005	Very low	48.22	17.74	56.53	21.71
RRMmsds	Li et al. (2009)	0.2685	Very low	55.44	29.22	68.51	37.42
	Tharion et al. (2009)	0.0417	Low	49.92	31.07	74.03	39.65
	Taelman et al. (2011)	0.5438	Very low	19.42	13.04	28.47	16.04
NN50p (%)	Tharion et al. (2009)	0.2152	Very low	20.21	19.07	39.03	23.02
	Taelman et al. (2011)	0.7842	Low	26.52	16.67	31.42	18.37
	Sieciński (2019)	0.3229	Low	15.36	14.42	37.06	21.54

2012). This makes an easier arrangement to compare the whole study on their way of approach that leads to an efficient understanding of each system along with their data analytic and signal processing capability (Burg et al., 2012; Fox et al., 2013; Garfinkel et al., 2014).

IV. Time-domain metrics

The meta-analysis includes a series of papers that are listed in the zone of time-domain of HRV analysis. Some of the measuring criteria are sorted out according to their relevance of use in different articles. Such zonal criteria are the mean of RR intervals (MeanRR), standard deviation of the RR intervals (RRStdd), square differences between root means square of the two successive RR intervals (RRMmsds), and proportion of RR intervals that differ more than a time period of 50 ms (NN50p), as depicted in Table 1.

The rigorous study that we have conducted leads to the fact that the MeanRR, NN50p, and RRMmsds get an enormous hike during the stressed condition, although some observations did not notice any difference in these features. By contrast, a reduced RRStdd was majorly observed in most of the studies (Chandola et al., 2010; Gabella, 2012; Grossmann

et al., 2016; Keller et al., 2011; Taelman et al., 2011; Tharion et al., 2009), involving time-domain analysis. Exceptions include the study by Schubert et al. (2009), which came up with an observation completely contradictory. Our general observation shows a subjugated incremental behavior of the RRStdd function (Goldberg & Grandey, 2007; Grossman & Taylor, 2007; Grossmann et al., 2016). Justification of this contradictory theory is also given by them, where the authors mentioned that a slow respiratory schematic and relative decrease in the ventilating mechanism was the main cause for achieving this result during the activity of public speech delivery.

V. Frequency-domain metrics

There are several papers that are shortlisted for quantification in frequency-domain analysis. The analytical feature of these quantifications is done on the basis of three regional distributions of the frequency-dominated signal. First, the signals are separated on the basis of low-frequency power area (LowF) and then segregated with respect to high-frequency power area (HighF), and finally, as a method of comparison, by the ratio between the HighF and the LowF.

Table 2 depicts the observation under such criteria. Among the papers listed, very few stated that

Table 2: The metrics considered in the frequency domain and their values under stress and rest conditions

Metric	References	Meta analysis report		Stress		Rest	
		Mean %-tile	Characteristics	Mean	Stdd	Mean	Stdd
LowF (ms ²)	Hjortskov et al. (2004)	8.52	Very low	1400	1030	1664	807.88
	Vuksanović (2007)	15.68	Very high	608	458.12	454.90	382
	Tharion et al. (2009)	5.75	Very low	1193	724.15	2155	2156
	Papousek et al. (2010)	14.25	High	1645	986.91	997.30	600.10
	Lackner et al. (2011)	10.16	High	1342	1205	813.17	650
	Traina et al. (2011)	15.32	Very high	1245	312	512	115
	Taelman et al. (2011)	14.82	Very low	468.10	460.20	869.53	641
HighF (ms ²)	Hjortskov et al. (2004)	5.42	Very low	1312	715	1775	1093
	Vuksanović (2007)	11.44	Very low	445	1081	638.90	1340
	Vuksanović (2007)	9.67	High	664.92	924.88	556.10	715
	Tharion et al. (2009)	1.52	Very low	1695	2093	2891	2623
	Li et al. (2009)	8.36	Very low	1202	1455	2002	2065
	Li et al. (2009)	11.80	Very low	1072	1056	1675	1752
	Papousek et al. (2010)	18.13	Low	667	402	1098	663
	Traina et al. (2011)	17.88	Low	253.15	264.20	277.60	245
	Taelman et al. (2011)	15.63	Very low	552	421	1001	785
HighF/ LowF	Sieciński (2019)	15.07	High	1157.22	2545.10	889.20	1526.24
	Hjortskov et al. (2004)	14.92	High	2.12	1.08	1.15	0.75
	Kofman et al. (2006)	20.19	High	1.61	1.02	1.12	0.68
	Vuksanović (2007)	4.67	Low	1.06	4.12	1.08	3.11
	Tharion et al. (2009)	12.76	High	1.32	0.78	1.40	1.78
	Schubert et al. (2009)	19.85	High	1.23	1.20	1.48	1.11
	Papousek et al. (2010)	23.10	High	1.14	0.63	0.01	0.76
	Traina et al. (2011)	4.65	Very high	6.12	2.88	3.10	2.10
	Sieciński (2019)	10.14	Very low	0.999	0.14	0.0005	0.0014

there is a considerable amount of increase in LowF with a statistical significance, whereas the other observation was completely contradictory with this fact. Tharion et al. (2009) observed perfectly normal general trends for the situations involved. Although, the fact has to be considered that the assessment of the readings done is taken on the day of the examination, the readings during the cause examination were completely ignored.

In accordance with that, Hjortskov et al. (2004) presented us with a completely different histology where there is an introduction session continued with the rest and stress situations. In the end, a noticeable dominant decrease in the low-frequency spectrum is vividly seen during the stress situation. To our knowledge, this situation arises due to the fulfillment of different protocols to simulate stress within the subject. Taelman et al. (2011) also support the factors behind these considerations.

In the HighF power domain, several studies agree with the fact that there will be a reduction in measure during acute mental activity or stress. An exception to this fact has also been registered in the study (Vuksanović, 2007).

Studies registered and analyzed on the basis of the HighF to LowF ratio criterion agree with the same fact unanimously that the signal measures increased during stress conditions (Tharion et al., 2009; Vuksanović, 2007), whereas the rest of the studies showed a different statistical analysis, which is not considered in conventional statistical analysis.

VI. Time-frequency domain metrics

A combined time-frequency metric is sometimes preferred to capture the temporal variation of the frequency components. These include short-time Fourier transform (STFT) and wavelet-based metrics.

Table 3: Different measures and definitions of the recurrence plot

Measure	Definition
Recurrence rate/recurrence points percentage in an RP corresponding to the correlation sum	$RR = \frac{1}{M^2} \sum_{i,j=1}^M R_{i,j}$
Recurrence points percentage forming diagonal lines	$REC_{det} = \sum_{q=q_{min}}^M qP(q) / \sum_{q=1}^M qP(q)$
Uncountable/the percentage of recurrence points which form vertical lines	$REC_l = \sum_{s=s_{min}}^M sP(s) / \sum_{s=1}^M sP(s)$
The proportion among DET and RR	$REC_{rate} = M^2 \sum_{q=q_{min}}^M qP(q) / \left(\sum_{q=1}^M qP(q) \right)^2$
Average length of the diagonal lines	$Q_{avg} = \sum_{q=q_{min}}^M qP(q) / \sum_{q=1}^M P(q)$
Average length of the vertical lines/trapping time	$TT = \sum_{s=s_{min}}^M sP(s) / \sum_{s=s_{min}}^M P(s)$
Length of the longest diagonal line	$Q_m = \max(\{q_i; i = 1, \dots, N_q\})$
Length of the longest vertical line	$S_m = \max(\{s_i; i = 1, \dots, N_s\})$
Divergence, related with the KS entropy of the system, i.e., with the sum of the positive Lyapunov exponents	$DIV = 1/Q_{max}$
ShnEn of the probability distribution of the diagonal line lengths $p(q)$	$E_n = -\sum_{q=q_{min}}^M P(q) \ln(P(q))$
The paling of the RR towards its edges	$RR_{trend} = \sum_{i=1}^U \left(i - \frac{U}{2} \right) (RR_i - RR_l) / \sum_{i=1}^U \left(i - \frac{U}{2} \right)^2$

M = total number of points on the phase space trajectory; N_q = total number of diagonal lines in the recurrence plot; N_s = total number of vertical lines in the recurrence plot; $P(q)$, $P(s)$ are diagonal/vertical line length's histogram and $U(x)$ = maximum number of diagonals parallel to the LOI, which will be taken for the computation of TREND.
ShnEn, Shannon entropy.

In the STFT method, the segmented signal of the mathematical expression in the continuous time-domain is given by $Y(t_c, t) = y(t)w(t_c - t)$, where t_c is in the middle of the real-valued, symmetric window function. The mathematical equation after using the Fourier transform on the segmented signal to restore its frequency properties is shown in the expression

$$Y(t_c, w_c) = \int_{-\infty}^{\infty} Y(t_c, t) e^{-jw_c t} dt$$

For QRS complex detection, a wavelet-based approach is generally preferred. Some preprocessing such as noise removal and removal of baseline wandering is required before the wavelet transform can be applied. Window detection by the method of determining QRS complex is given by

$$W(m, n) = \int_{-\infty}^{\infty} f(y) \phi_{m,n}^* \phi_{m,n}(y) dy, \text{ where the function of RR interval is given as } W(t) = \sum_{i=1}^n \delta \left[t - \sum_{n=1}^i y(n) \right].$$

VII. Non-linear domain metrics

The non-linear analysis involves the application of non-linear system theory, such as chaos theory, to quantify non-stationary HRV signals. The HRV dynamics can be characterized in the non-linear domain, maintaining clinical utility through Poincare plots, short-term fractal scaling exponent measured with detrended fluctuation analysis (DFA), the Lyapunov exponent, and different entropy

Table 4: The metrics considered in the non-linear domain and their values under stress and rest conditions

Metric	References	Meta analysis report		Stress		Rest	
		Weight	Characteristics	Mean	Stdd	Mean	Stdd
D1(-)	Vuksanović (2007)	0.5049	Very high	1	0.17	0.90	0.18
	Melillo et al. (2011)	0.4942	Very low	1.04	0.45	1.43	0.17
D2(-)	Schubert et al. (2009)	0.5413	Very low	3.3	0.34	3.42	0.29
	Melillo et al. (2013)	0.4590	Very low	1.62	1.30	2.92	1.07
	Melillo et al. (2011)	-	Low	0.74	0.12	0.76	0.19
En(0.2) (-)	Melillo et al. (2011)	-	Very low	1	0.30	1.10	0.14
En(rchon) (-)	Melillo et al. (2011)	-	Very low	1	0.25	1.17	0.12
En(rmax) (-)	Melillo et al. (2013)	-	Low	1.06	0.18	1.15	0.14
LLE	Vuksanović (2007)	-	High	0.05	0.018	0.05	0.017
Lmax (beats)	Melillo et al. (2011)	-	Very low	213.30	137.12	285.90	111.32
Lmean (beats)	Melillo et al. (2011)	-	Very high	14.90	6.82	11.07	2.47
RECdet (%)	Melillo et al. (2011)	-	High	98.57	1.30	98.70	0.87
RECrates (%)	Melillo et al. (2011)	-	Very high	42.30	12.80	33.49	6.30
SampEn (-)	Vuksanović (2007)	-	Very low	1.72	0.05	1.80	0.03
SD1 (ms)	Melillo et al. (2011)	-	Very low	0.03	0.02	0.04	0.02
SD2 (ms)	Melillo et al. (2011)	-	Very low	0.06	0.02	0.09	0.04
ShnEn (-)	Melillo et al. (2011)	-	Very high	3.46	0.40	3.18	0.24

ShnEn, Shannon entropy.

measures such as Shannon entropy (ShnEn) and sample entropy.

a. Poincare plot and recurrence plot

Standard deviation in the case of the Poincare plotting system and the recurrence method are linear in nature and defined by SDstd and SDrec, respectively. More than three state space trajectories can be reduced down to only two dimensions by this method of recurrence plot. The methodology is depicted as $R_{i,j} = 0, w_i - w_j > \varepsilon; R_{i,j} = 1, w_i - w_j \leq \varepsilon$. Here in the formulation, only two states i and j are shown although it can be done for the higher number of states. The method needs a threshold value ε that is user defined according to the situation. Lengths of the distance between two trajectories are calculated, and if the value is less than the threshold it will be taken as 1 while if it is greater than ε then it will be taken as 0. Table 3 explains different measures of recurrence plot and their definitions.

The determination of the recurrence plot like Figure 4 is given by RECdet (Hautala et al., 2009;

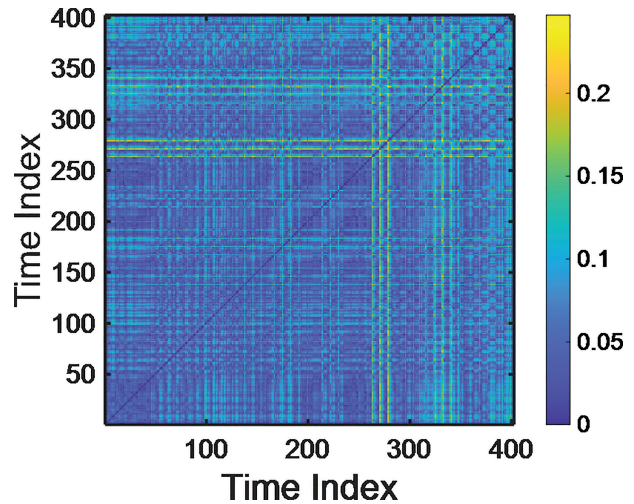


Figure 4: Recurrence plot of the data analyzed.

Lehrer et al., 2006) along with that the recurrence rate is also defined as RECrates in an approved condition, where the length of lines (Lmax) can be considered

as a defining criterion, while the lines' mean length (Lmean) plays a vital role in that system.

The quantification of two-dimensional (2D) and three-dimensional (3D) Poincare plotting are given as $e^+ = |E(j)|_{j=1+\tau}^N, \tau = 1, \dots, (N-1)$, where $|E(j)|_{j=1}^N$ is a representation of a discrete signal, and e^+ and e^- are subgroups of the discrete signal with time delay τ . The system of coordinates is replaced with a two-dimensional rotation with an angle of $\pi/4$ with respect to X-axis, i.e.,

$$\begin{pmatrix} e_m \\ e_n \end{pmatrix} = \begin{pmatrix} \cos(\pi/4) & -\sin(\pi/4) \\ \sin(\pi/4) & \cos(\pi/4) \end{pmatrix} \begin{pmatrix} e^+ \\ e^- \end{pmatrix}.$$

On the other hand, 3D Poincare plotting has been done by the method of ellipsoid fit, shown in Figure 5.

In the new coordinate used in the system, $Em' = \text{Mean } Em$, $En' = \text{Mean } (En)$, $SD1 = [\text{Var}(Em)]^{1/2}$, $SD2 = [\text{Var}(En)]^{1/2}$, where $|E(j)|_{j=1}^N$ is a representation of discrete signal and e^+ , e^- , and e^{--} are subgroups of the discrete signal with time delay τ . Further, $e^+ = |E(j)|_{j=1}^{N-2\tau}$, $e^- = |E(j)|_{j=1+\tau}^{N-\tau}$, and $e^{--} = |E(j)|_{j=1+2\tau}^N$, with $\tau = 1, \dots, (N-1)$.

b. Entropy

A mathematical formulation of ShnEn can be obtained as follows. The definition of energy for discrete-time ECG signal, $x[n]$, may be represented in the following manner (Beyramienanlou & Lotfivand, 2017):

$E_x = \sum_{n=-\infty}^{\infty} [x_n \cdot x_n^*] = \sum_{n=-\infty}^{\infty} [x_n]^2$. To find ShnEn, zero-phase filter and Shannon energy approximate are playing a vital role. Considering $a[n]$ as the filtered and normalized version of $x[n]$, the energy of the local spectrum for an individual sample is $\text{ShnEn} = -|a[n]| \log(|a[n]|)$. The process output, $s[n] = -a^2[n] \log(a^2[n])$, is further normalized, $s[n] = (s[n] - \mu)/\delta$, where μ is the process normalization vector. Next, a rectangular filter of length h is used to diminish the spikes. The filtering operation is $m[n] = \text{filter}(h, j, S)$, where $m[n]$ defines moving average. The diagnosed peaks are linked together by the difference equation, $d[n] = f[n] - f[n-1]$, $n = 2, 3, 4, \dots$, where $f[n]$ is the input to the Shannon energy calculation process.

To detect QRS complex in non-linear domain, the threshold selection has to be made by the following relations: $\text{Threshold} = |k\mu(1 - \sigma^2)|$ if $\sigma < \mu$, or $\text{Threshold} = |k\sigma(1 - \mu^2)|$ if $\sigma > \mu$, where k is a constant. The largest Lyapunov exponent is LowEmax, where the dimension correlation is D2. The fluctuation correlation can be done in short- and long-term modes.

The approximate entropy, $En(\text{rchon})$, was devised by Chon et al. (Chon et al., 2009), where the tolerance threshold (r) has been set to 0.03 NNstd to obtain the maximum entropy value. These calculations by the embedding dimension methodology are indicated in Figure 6. The methodological technique is as follows. In this case, we initialize from a scalar time series placed in a

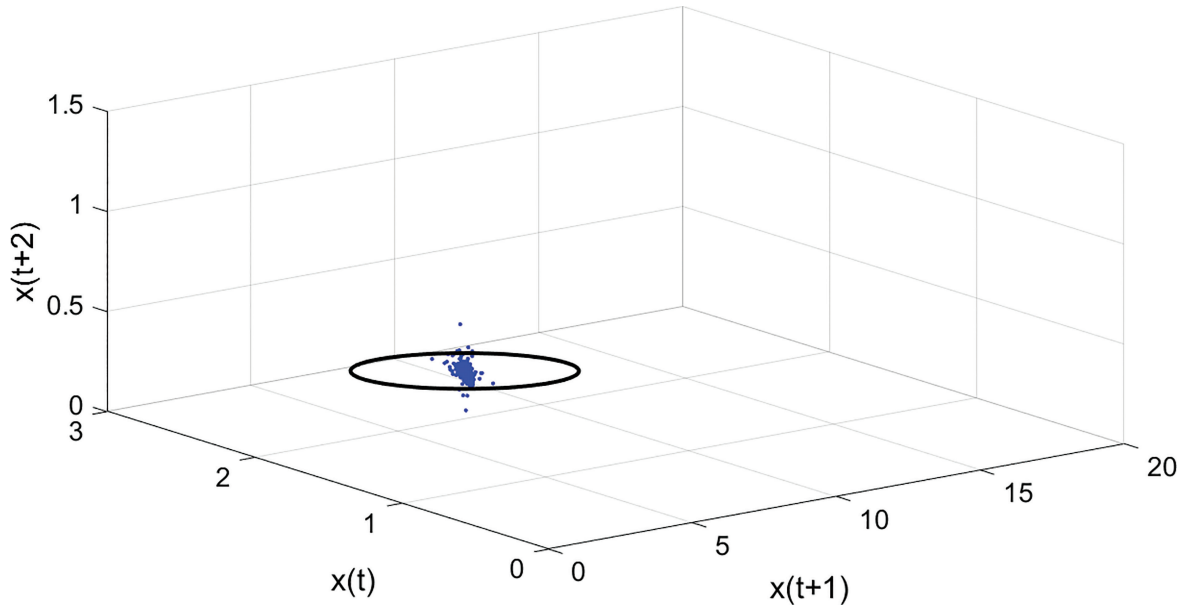


Figure 5: Ellipsoid fit applied on the dense region.

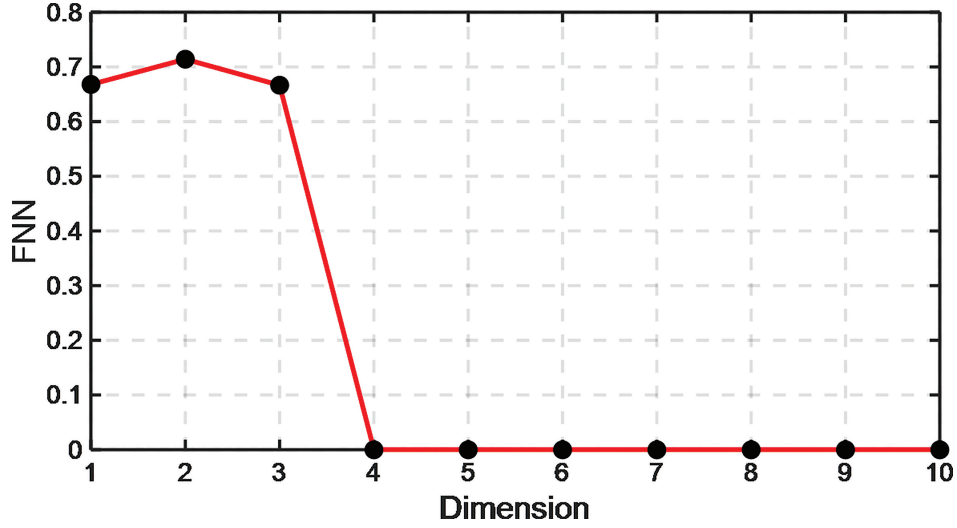


Figure 6: False nearest neighbor test.

m -dimensional phase space using a time-delay procedure, where the number of points placed in the m -phase space is $N = N_c - (m - 1)h$, where h is the time-delay represented as multiple of time interval. The correlation between them is expressed by:

$$C_m(r) = \lim_{n \rightarrow \infty} \frac{2}{N(N-1)} \sum_{i=1}^N \sum_{j=i+1}^N \Theta(r - |y_i - y_j|), \text{ where } r \text{ is}$$

the correlation length. In most of the conditions, $C_m(r)$ grows as a power of r . Thus, a plot of $\log(C_m(r))$ vs $\log(r)$ shows the scaling region, $\log(C_m(r)) \approx D_2 \log(r)$. By this methodology, we can define the number of false neighbors in the system to its embedding dimension (D2; Casaleggio et al., 1995).

The two features, namely, entropy at the maximum threshold, $En(r_{max})$, and the max Entropy reported by Chon et al., $En(r_{chon})$, are explored in various studies (Melillo et al., 2011; Papousek et al., 2010), which reported a decrease in Std under stress. Melillo et al. (2011) and Schubert et al. (2009) have taken their signals while performing an academic examination and arithmetic task, respectively. In a different paper, the same author (Melillo et al., 2013) reported a completely different trend, and the study by Vuksanović et al. (2007) confirmed the opposite trend. Different characteristics of non-linear parameters are expressed in Table 4.

c. Other parameters

Studies of two research papers (Melillo et al., 2011; Traina et al., 2011) showed that manual analysis is

not required for the analysis of HRV during stress while mathematical modeling can be done, which can automatically isolate the signal segments during stress. It has been proposed by Melillo et al. (2011) that a model based on linear discriminate analysis (LDA) considers the measures of the HRV domain in the non-linear tone, namely D1, D2, and En (0.2). This model achieves maximum robustness, sensitivity, and specific accuracy of about 92%, 87%, and 94%, respectively. This model has the ability to detect the stress area automatically, isolating it for the convenience of the user. These methodologies were cross verified 10 times to check the validity of this kind of classifier-based techniques. Traina et al. (2011) studied the person correlation, which was accessed in high and low areas of the power spectrum under frequency domain. This was done after the experimental sessions had been completed successfully, explaining the correlation between them. However, this is a matter of controversy as Pearson correlation works on the chaotic behavior of the HRV signals usually when HRV signals cannot be accessed with a regular analytical technique.

VIII. Comparison between time-, frequency- and non-linear-domain metrics for cognitive tasks

Our current study presents a schematic literature review of investigated articles in a meta-analytic way.

We present how HRV signals are manipulated under artificial mental stress.

In the time-domain, the report measures four HRV metrics, namely RRStdd, RRMmsds, NN50p, and D2, which depict a unique behavior during stress conditions (Chandola et al., 2010; Li et al., 2009; Papousek et al., 2010; Schubert et al., 2009; Taelman et al., 2011; Tharion et al., 2009). The sample selection of the study coincides with the fact that there is a major decrease in the normal properties of RR signals during the zone of stress. Specifically, RRStdd (Schubert et al., 2009) was the measure where there is a significant decrease shown during stress.

The same characteristics have also been noticed in the HighF frequency-domain analysis (Chandola et al., 2010; Hjortskov et al., 2004; Li et al., 2009; Papousek et al., 2010; Taelman et al., 2011; Tharion et al., 2009), while the HighF/LowF ratio and the LowF itself have shown a significant behavior, during stress, which is increasing in nature (Chandola et al., 2010; Hjortskov et al., 2004; Kofman et al., 2006; Lackner et al., 2011; Li et al., 2009; Papousek et al., 2010; Traina et al., 2011; Vuksanović, 2007). HRV measures are mostly taken for 5 min (Schubert et al., 2009), while in this case, it has been taken for 3 min (Chandola et al., 2010; Taelman et al., 2011; Tharion et al., 2009) by the respective researchers. Coming to the domain of LowF, certain experts' studies pointed out a major lowering in the behavior during stressed conditions (Hjortskov et al., 2004; Taelman et al., 2011; Tharion et al., 2009), while others reported a different scenario (Lackner et al., 2011; Li et al., 2009; Papousek et al., 2010; Traina et al., 2011; Vuksanović, 2007). Although their mode of study is completely different from the others, the first and the second ones used physical stress to mimic stress conditions, while the others used arithmetic tests to simulate stress. In the first work, Hjortskov et al. (2004), the volunteers were asked to perform a typing task with their dominant hand on the non-dominant section of a keyboard at a relatively fast pace under a time constraint. On the contrary, to simulate stress, participants have to choose a correct answer from the alternatives given to a question by clicking the mouse but not with their dominant hand. This activity seems to activate a different article that had not been activated when they were asked to use their usual working hand, as depicted by Taelman et al. (2011). An important observation is that no physical activity has been involved in this process. A majority of the studies asked their subjects to perform a mathematical test using only the

keyboard. This experiment has been performed by Yu and Zhang (2012). On the other hand, a single study reported a decreased HRV during stress with a LowF value less than the usual stress condition. In this situation, the performers were the students of the university, and their HRVs are jotted on the day of their examination by Tharion et al. (2009) and Acharya et al. (2006). This experiment focused on the examination day but failed to report the conditions of the pupil during the examination (Balda et al., 1977; Melillo et al., 2011). These properties of the layering of stress-building procedures were delivered in Bracha (2004). Each of these layerings has a different and unique impact on HRV modulation when studied on ANS. The values of HRV measures are projected in different aspects in two different unique papers (Melillo et al., 2011; Vuksanović, 2007). Both of these papers have significant statistical significance. But the clarity of such heterogeneous results was not identified in this paper. The measures that are tabulated can be considered as a checkpoint for further researchers in this area (Bando et al., 2015; Bland & Altman, 1996; Blaug et al., 2007; Castaldo et al., 2015, 2016; Crowley et al., 2011; Jelinek et al., 2011; Melillo et al., 2012; Pan & Li, 2007; Raaijmakers et al., 2013; Satya, 2009; Siegel & Castellan, Jr., 1988; Sinha et al., 2016).

HRV measures like RRStdd, RRMmsds, NN50p, D2, HighF, LowF, and HighF/LowF are the seven significant metrics through which meta-analysis of the pooled values has been done. Thus, the values pooled together can be considered more reliable rather than picking on the values from the individual paper. Although the values received by the HighF/LowF measures are statistically significant, the differences in measurement were too small when compared to the measures of RRStdd during rest as well as stress (Singh et al., 2013). The values determined by the LowF measures can be considered effective if it is applied to different system designs (Hjortskov et al., 2004; Taelman et al., 2011).

From the above-measuring aspects, the non-linear analysis was found to be the most robust and apt system, as every analytical procedure in the non-linear domain shows similar results for all measures. From the study, it can be concluded that an analytical study of the cardiac signals can prove to be an elementary tool for diagnosis (Bishop, 2006; Eckberg, 1983; Garcia-Mancilla & Gonzalez, 2015; Hernández-Vicente et al., 2021; Liu & Ulrich, 2014; Salahuddin et al., 2007; Sano & Picard, 2013; Sinha et al., 2015; Tabar & Halici, 2016; Timothy et al.,

2016). Moreover, the effect of human stress on the chaotic biological signals can be effectively measured with the aid of non-linear-domain analysis of the same (Barreto et al., 2007; Bousefsaf et al., 2013; Healey, 2015; Kelsey et al., 2004; Laird et al., 2005; McDuff et al., 2014; Nunan et al., 2010; Quintana & Heathers, 2014; Thayer et al., 2012). The accuracy of the non-linear metrics can significantly benefit the medical community.

IX. Conclusions

We would like to conclude that the papers investigated in this study show a unanimous report on the non-linear measures of HRV, and they all proved that there is a significant deviation in it during acute mental stress. In the case of non-linear studies, where the same stress has been incorporated to manipulate the situation, the conclusions achieved are much more robust and give better results than the frequency-domain analysis. The situation can be simulated, or the stress condition may occur naturally, but the results in the non-linear domain are more accurate than that of the frequency-domain without any changes in the condition. The situations support the prior observations in this area, which proves that a shift has always been incorporated in ANS, maintaining a balanced equilibrium in the parasympathetic activation while maintaining avoidance while the subject is under stress. As we have seen, these non-linear studies can efficiently point out those shifts. Although various case studies studying the psychological effects of human stress have been incorporated in this study, a few more methodologies have not been used in the field of HRV analysis. Thus, this study provides a rigorous benchmark for future researchers to work on this field of non-linear activities of HRV and its characteristics during mental stress.

Although we have given a brief idea about the techniques used for HRV analysis, we have not developed any predictive model or analytical technique to support a correlation between the processes involved. To defeat these impediments, in future psychophysiological experiments, it will be helpful to use the arising rules for detailing HRV boundaries (Laborde et al., 2017), which can improve the nature of information, permit more straightforward announcing, and lead to more analyzable information in the quantitative investigation (e.g., meta-examination). Further examination should plan to build the investigations on the connection between HRV and some

psychological areas, like consideration, language, preparing speed, and visuospatial abilities that are dismissed by the examinations up to this point.

Declarations

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Authors' Contributions

All authors have participated in (a) conception and design, or analysis and interpretation of the data; (b) drafting the article or revising it critically for important intellectual content; and (c) approval of the final version.

Conflict of Interests

The authors have no affiliation with any organization with a direct or indirect financial interest in the subject matter discussed in the manuscript.

Ethical Approval

The research does not involve human participants or animal experimentation; hence no ethical clearance is required.

Availability of Data and Materials

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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