In: A Closer Look at Heart Rate
Editor: André Alves Pereira
ISBN: 978-1-53616-979-9

Chapter 1

SHORT-TERM RESTING-STATE HEART RATE VARIABILITY

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ABSTRACT

Resting-state heart rate variability (HRV) has been proposed as a predictor of behavioral and cognitive responses in various experimental tasks. Specifically, high resting-state HRV has been associated with enhanced cognitive control in tasks requiring working memory, voluntary

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attention, and inhibitory control. HRV can be analyzed in the time-domain as well as frequency-domain using linear or non-linear indices. The resting-state condition has been operationally defined as relaxing quietly with eyes-closed or eyes-open. Differences among HRV indices and the definition of resting states tend to undermine efforts to link resting-state HRV and performance in cognitive control tasks in terms of predictive ability and consistency. In the current study, we examined the latent structures underlying short-term HRV indices in a sample of 96 young adults (43 women; average age 25.69 $\pm$ 4.32) under 4-min eyes-closed followed by 4-min eyes-open resting-state conditions. Electrocardiograms (ECGs) recorded during the two resting-state conditions were then analyzed using a variety of HRV indices, of which latent structures were identified using principal component analysis. Our results revealed that time-domain indices were robust to resting-state conditions and provided clear measurements within a single dimension, whereas frequency-domain and non-linear indices measured different dimensions according to whether the participant was relaxing with eyes-closed or eyes-open. Participants also completed questionnaires pertaining to state-trait anxiety, self-referential thoughts, and behavioral inhibition/activation before/after obtaining the resting-state ECG recordings. The HRV dimensions differed in the way they related to scores obtained on these psychological scales. The latent dimensions that were strongly associated with non-linear HRV indices were better predictors of scale scores, compared to dimensions that were more strongly associated with indices in the time-domain and frequency-domain. Our results have suggested that short-term resting-state HRV indices measure different aspects of physiological and psychological states in human participants. It appears that latent dimensions of short-term resting-state HRV indices may be used as regressors to predict cognitive, affective, and behavioral responses in experimental tasks.

Keywords: behavioral inhibition system, heart rate variability, resting-state conditions, self-referential thoughts

INTRODUCTION

Heart rate variability (HRV) refers to the variations in successive inter-beat intervals within electrocardiogram (ECG) time series, which can be considered as a physiological index for monitoring autonomic activity (Camm et al. 1996; Acharya et al. 2006). HRV indices have been used as markers for cardiac vagal activity in human participants under various psychological conditions such as social engagement (Kemp et al. 2012), the perception of affective stimuli (Park, Van Bavel, et al. 2013; Park and Thayer 2014), and emotion regulations (Williams et al. 2015). These indices can also be used to predict affective instability in daily life (Koval et al. 2013). Previous studies have treated resting-state HRV as a psychophysiological phenomenon characterizing the degree of vagal activity prevailing over sympathetic activity (Thayer et al. 2012; Thayer et al. 2009). High resting-state HRV is accompanied by enhanced cognitive control over tasks requiring working memory, selective attention, or inhibitory control (Hansen et al. 2004; Hovland et al. 2012; Park, Vasey, et al. 2013; Colzato et al. 2018). Research has shown that chronic reductions in vagal activity are associated with poor physiological, emotional, cognitive, and behavioral regulations, which can result in low self-rated health (Alvares et al. 2013; Jarczok et al. 2015; Thayer et al. 2012; Thayer et al. 2009) and a high risk of psychopathology (Beauchaine and Thayer 2015; Kemp et al. 2010; Koenig, Kemp, Feeling, et al. 2016; Koenig, Kemp, Beauchaine, et al. 2016; Clamor et al. 2016). Overall, HRV is associated with a wide range of psychophysiological functions related to general well-being in humans.

HRV analysis has been recommended for long-term (24-hr) as well as short-term (5-min) recording procedures (Camm et al. 1996). While 24-hr HRV analysis is helpful for increasing resolution in the frequency-domain and particularly in the low frequency range, it is difficult to be implemented in typical volunteers. The short-term ECG recording procedure is more practical than the long-term procedure, offering a number of notable advantages: (i) relative ease in recording, (ii) convenience in controlling confounding factors, such as variations in the physical or mental states of experimental participants and in the recording environments, (iii) computational efficiency in data processing, and (iv) flexibility in visualizing dynamic changes in HRV within a short period of time (Li, Rüdiger, and Ziemssen 2019). Short-term and long-term HRV recordings have both been widely used in clinical settings. One factor that is commonly overlooked is the "set point" (or resting baseline) of normal HRV, which is itself regulated by the body's negative feedback mechanism to maintain homeostasis (Zhang 2007). Crucially, the set point is not changed by short-term fluctuations in the heart rate other than trauma (Antelmi et al. 2004; Tuomainen et al. 2005). In this chapter, we focus on short-term HRV indices which are independent of the influence of day-to-day activity, a factor that may crucially affect the validity of long-term recordings.

Few ECG studies have clearly specified eyes-closed or eyes-open conditions as the resting-state baseline in HRV measurements. One previous study reported that the high-frequency (HF) power was higher under the eyes-closed resting state than under the eyes-open resting state (Amin et al. 2013). That study also reported that the low-frequency (LF) power and LF/HF ratio were higher under eyes-open than under eyes-closed conditions. We reported similar findings in terms of HF, LF, and LF/HF ratio expressed in normalized units (Liou et al. 2018). The HF power has conventionally been used as an index for parasympathetic (i.e., vagal) dominance, whereas the LF power and LF/HF ratio are used as indices for sympathetic dominance (Camm et al. 1996; Acharya et al. 2006). Another study compared the effect of eyes-closed and eyes-open resting states on mental fatigue by obtaining ECG readings before and after assigned tasks (Mizuno et al. 2014). The authors reported no variations in sympathetic or parasympathetic sinus modulation during the pre-task rest period under eyes-open or eyes-closed conditions. Nonetheless, the authors reported that during the post-task rest period, sympathetic nerve activity was higher and parasympathetic nerve activity was lower under eyes-open than under eyes-closed conditions. This difference was attributed to variability in attentional levels associated with the two conditions, wherein sympathetic nerve activity was thought to be higher under the eyes-open condition than under the eyes-closed condition (Hori et al. 2005). Thus, it is possible that the eyes-closed resting-state (baseline) condition could be used as a proxy for parasympathetic activity, whereas the eyes-open resting-state (baseline) condition could be used as a proxy for sympathetic activity. Those studies have provided preliminary evidence that results obtained under eyes-open and eyes-closed conditions should be analyzed separately; that is, they should not be combined for resting-state analysis.

According to a recent report, cardiovascular diseases (CVDs) are among the leading causes of death worldwide for men and women (Mozaffarian et al. 2015). However, the onset of CVDs affects the health of men and women differently, with the result that the prevalence of CVD-related mortality and morbidity is higher and tends to occur earlier in men (Berry et al. 2012; Mikkola et al. 2013). One recent meta-analysis on gender differences (Koenig and Thayer 2016) in HRV among healthy controls (10-74 years) revealed several interesting findings. In time-domain HRV indices, the mean RR interval and standard deviation of RR intervals (SDNN) were significantly lower among women on the average. The spectral power density of HRV was characterized, on the average, by a significantly lower total power, a significantly higher HF power and a significantly lower LF power. These effects were also manifested as the lower LF/HF ratio. Overall, women showed greater vagal activity, as indexed by higher HF powers in HRV readings. The authors concluded that the autonomic control of female hearts is dominated by parasympathetic activity (in spite of the higher mean heart rate), whereas male hearts are dominated by sympathetic activity (in spite of the lower mean heart rate). The heart rates (HRs) of women are generally higher than those of men; however, their risk of CVDs is not higher (Cordero and Alegria 2006). Thus, it appears that the HR does not have the same predictive power for mortality and morbidity in women as it does in men (Sacha 2014). This paradoxical situation warrants additional research involving the analysis of gender differences in the autonomic control of the heart, as indexed by HRV.

In the past three decades, there have been a number of independent reports on the age influence on short-term HRV recordings (Migliaro et al. 2001; Schwartz, Gibb, and Tran 1991; Zhang 2007; Antelmi et al. 2004). It appears that time-domain HRV indices, such as SDNN, root mean square of successive RR differences (RMSSD), and the proportion of successive RR intervals that differ by more than 50-ms (pNN50), consistently decrease with age, whereas the mean RR interval increases with age. Among the frequency-domain indices, it appears that HF, LF, and very-low-frequency (VLF) powers consistently decrease with age. The LF/HF ratio does not present this age decline effect, however. Some studies have demonstrated age-related and gender-related variability in short-term HRV, both of which have significant effects on most linear and non-linear HRV indices (Voss et al. 2015; Voss et al. 2012). For example, research reported significant increases in detrended fluctuation analysis (DFA) indices (i.e., α_1 and α_2) across five age groups ranging from 25 – 74 years (10-year intervals). Poincare plot analysis indices (SD_1 and SD_2) presented similar decreases across age groups. Significant gender differences were observed in DFA_α_1 results among participants ranging in age from 25 – 64 years. Gender differences were not observed with SD_1, SD_2, or DFA_α_2 indices. These results have highlighted the degree to which gender and age can affect short-term HRV indices, and have also underlined the importance of considering these factors in any study based on HRV. In this chapter, we focus on young adults (19-39 years), due to the fact that this age group presents the highest HRV on all of the time-domain, frequency-domain, and non-linear indices (Voss et al. 2012; Voss et al. 2015).

Self-referential processes are those associated with stimuli that are experienced as strongly as that of real-life experiences. For example, the way we perceive pictures of ourselves with close friends versus pictures of a random people on the street, or pictures of a home where we spent most of our childhood versus random houses on the street. Meta-analysis of fMRI studies has revealed considerable overlap between the neural correlates of self-referential processing and those associated with the default mode network (Gusnard and Raichle 2001; Raichle et al. 2001), including brain regions that are functionally active even under the resting-state conditions. There is also considerable overlap between the EEG correlates of self-referential processing and the anterior hub of the default-mode network, particularly in the medial prefrontal cortex (Knyazev 2013; Knyazev et al. 2012). In the time-domain, distinguishing between self- and others-related information is associated primarily with the P300 ERP component. In the frequency-domain, spontaneous self-referential processing is associated primarily with lower spectral powers in the theta and alpha frequency bands (Bocharov et al. 2019; Knyazev et al. 2012). Previous research reported minor differences in brain regions in the default mode network (Bluhm et al. 2008) across ages and genders. It is important to examine the role of self-referential processing in HRV dimensions.

Anxiety is a feeling of apprehensive uneasiness triggered by stressful events or anticipated failures. State-anxiety is defined as a transitory emotional state arising from threatening or dangerous situations marked by increases in the HR and/or respiration. One study on recognizing emotions in faces reported that participants experiencing state-anxiety (i.e., with elevated amygdala responses) were more likely to categorize faces as fearful (vs. neutral), regardless of attentional focus (Bishop, Duncan, and Lawrence 2004). Trait-anxiety refers to a stable tendency to recognize and report on negative emotions that are largely independent of specific situations. Trait-anxiety is related to increased arousal levels in the behavioral inhibition system (BIS), which is particularly pronounced in cases of decision-making under uncertainty. Trait-anxiety can affect cognitive outcomes by overestimating negative effects in ambiguous situations (Gray 1982). Previous research based on the reinforcement sensitivity theory has addressed the well-defined role of the BIS; however, the behavioral activation system (BAS) is less well-defined, particularly in terms of reward versus impulsivity (Taubitz, Pedersen, and Larson 2015). In one study on the neural correlates of BIS and BAS, it was reported that BIS was uniquely related to the N2 ERP component on NoGo trials of a Go/NoGo task, linking BIS to conflict monitoring as well as sensitivity to NoGo cues (Amodio et al. 2008). In that study, it was reported that higher BAS scores were uniquely associated with pronounced left-sided baseline frontal cortical asymmetry associated with approach orientation. However, it remains unclear how BIS/BAS is related to resting-state HRV. Several HRV indices have consistently indicated reduced vagal activity and elevated sympathetic activity under anxiety-provoking situations, suggesting that there is a negative relationship between cardiac vagal control and trait-anxiety (Friedman 2007). Anxiety disorders are generally associated with a decrease in HRV (Chalmers et al. 2014) by showing a shift from autonomic balance toward increased sympathetic activity, as characterized by the high LF power. It is important to investigate in young adults the link between resting-state HRV and their anxiety as well as BIS/BAS traits.

Short-term HRV can be analyzed in the time-domain and frequency-domain using linear or non-linear indices. As mentioned, resting states have been operationally defined as relaxing quietly under eyes-closed or eyes-open conditions. Variations in HRV indices and the definitions of resting-state conditions have led to an inconsistency among studies linking resting-state HRV to cognitive control. This study was intended to assess the latent structures underlying short-term HRV indices under either eyes-closed or eyes-open conditions. We analyzed ECGs from 96 young adults (43 women; average age 25.69 ± 4.32) whose data were recorded previously in two separate experimental studies. One study involved tasks on ambiguous sentence detection while the other investigated emotional inhibition. In both studies ECG recordings were obtained while the participants were resting quietly under 4-min eyes-closed followed by 4-min eyes-open conditions. The State-Trait Anxiety Inventory (STAI) (Spielberger and Gorsuch 1983) was administered prior to the ECG recording. After the ECG recording, 57 participants from the first study were assessed using the Self-Referential Thought Questionnaire (STQ), whereas 39 participants from the second study were assessed using the BIS/BAS scale. As in previous reports (Young and Benton 2015), we expected that adding non-linear indices to linear HRV indices would aid in predicting behavior responses on these psychological scales. We also examined the effects of gender, age, and resting-state condition on HRV indices. Finally, we sought to determine the appropriate use of HRV latent dimensions under eyes-closed and eyes-open conditions for scientific or clinical inquiry.

METHODS

Participants

A total of 96 right-handed, neurologically normal adults were recruited in the EEG experiment as a part of two separate cohorts. The first cohort was formed of a sample of 57 participants in a language study while the second one was formed of a sample of 39 participants in an emotional inhibition study. All participants were undergraduate or postgraduate students without a history of psychiatric and neurological disorders. Specifically, the sample included 43 women aged 19–35 (average age 24.07 ± 3.863) and 53 men aged 20–39 (average age 27 ± 4.256). All participants provided informed written consent before enrollment in the study. The experiment was approved by the Human Subject Research Ethics Committee/Institutional Review Board at Academia Sinica, Taiwan, in accordance with the Declaration of Helsinki.

State-Trait Anxiety Inventory

The Chinese version of the State-Trait Anxiety Inventory (cSTAI) was used to assess the explicit anxiety levels of participants (Spielberger and Gorsuch 1983; Shek 1993). In the inventory, the 20-item STAI-Trait scale targets how participants generally feel, whereas the 20-item STAI-State scale assesses how participants feel at the time they took the inventory. State and trait anxiety scores were both considered in regression analysis, and a larger score indicated a higher anxiety level. On the cSTAI, participants were asked to rate themselves on each item based on a 4-point Likert scale, ranging from rarely to almost always. The STAI has been clinically validated in several studies (Grös et al. 2007; Kvaal et al. 2005). The STAI is socially and culturally dependent, that is, different ethnic groups present different norms. The 96 participants in this study were from the same cultural group; therefore, we used the cSTAI to evaluate relative differences among participants in terms of anxiety levels.

Self-Referential Thought Questionnaire

The Self-Referential Thought Questionnaire (STQ) was designed to measure various aspects pertaining to one’s thoughts and feelings while undergoing spontaneous EEG/ECG registration under resting-state conditions (Knyazev 2013; Knyazev et al. 2012). All items were measured using a five-point Likert scale. The results of factor analysis of all questionnaire items (principal factor analysis with varimax rotation) conducted in a large sample (N = 160) revealed that a four-factor solution best fitted the data (Knyazev and Slobodskaya 2003). From the original 37 items in the questionnaire, we selected 29 items that had high loadings on a single factor. The subscale "emotions" includes 10 items used to measure the emotional response of participants during the ECG recording. Examples of typical responses are "I experienced negative emotions during the recording" and "I was calm and relaxed during the recording." A higher score indicates that the emotion(s) experienced by the participant tended to be positive. The subscale "self-referential thought (SRT)" includes 8 items used to measure intrinsic processes. Examples of typical responses are "I occasionally tried to recall things in front of me during the recording" and "I thought about employment or university problems during the recording." A higher score indicates that the participant was less able to recall events or things encountered in his/her daily life. The subscale "attention (ATT)" contains 6 items used to measure attentiveness to the recording procedure. Examples of typical responses are "During the recording, I paid attention to external odors most of the time" and "I felt hot during most of the recording." A higher score indicates that the participant paid less attention to the recording procedure. The subscale "drowsiness" contains 5 items used to reveal the physiological state of the participants. Examples of typical responses are "During the recording, I was very aroused" and "I was dozy during most of the recording." A higher score indicates that the participant was more aroused.

Behavioral Inhibition System and Behavioral Activation System (BIS/BAS) Scale

The behavioral activation system is believed to regulate appetitive motives, wherein the goal is to move toward something desired. The behavioral inhibition system (or avoidance) is said to regulate aversive motives, wherein the goal is to move away from something unpleasant. We used the 24-item BIS/BAS scale (Carver and White 1994) to assess individual differences in the sensitivity of these systems with respect to resting-state HRV under eyes-closed or eyes-open conditions. Factor analysis conducted on a large number of college students (N = 732) yielded four factors (Carver and White 1994). The BIS subscale contains 7 items used to measure the degree of social withdrawal. Examples of typical responses are "I have fewer fears than do my friends" and "I worry about making mistakes." A higher score indicates that the participant would be more likely to inhibit movement toward a goal. The BAS subscale (Reward Responsiveness) contains 5 items used to measure positive responses to a reward. Two typical responses are "It would excite me to win a contest" and "When I see an opportunity to get something I want, I become excited right away." A higher score indicates that the participant was prone to adaptive impulsivity. The subscale BAS_drive contains 4 items used to measure strong pursuit of appetitive goals. Examples of typical responses are "I go out of my way to get things I want" and "If I see a chance to get something I move toward getting it right away." A higher score indicates that the participant was prone to dysfunctional impulsivity. The subscale BAS_fun_seeking contains 4 items used to measure one's ability to seek out potentially rewarding situations and act without advance preparation or deliberation. Examples of typical responses are "I often act on the spur of the moment" and "I crave excitement and new sensations." A higher score indicates that the participant was prone to functional impulsivity.

EEG/ECG Recording

Following completion of the cSTAI, participants sat comfortably with eyes open in a chair positioned 60 cm in front of a computer screen in a sound-insulated chamber. Electroencephalograms (EEGs) and electrocardiograms (ECGs) were recorded using an EEG cap with 132 Ag/AgCl electrodes (including 122 10–10 system EEG, the bipolar VEOG, HEOG, ECG, EMG, and six facial-muscle electrodes). The EEG electrodes were placed in 122 sites according to the extended international 10–10 system and were referred to as Cz with ground at FzA. Bipolar ECG electrodes were placed on the back of both the left and right hands of participants. Electrode resistance was maintained below 5 kΩ. Signals were amplified using Neuroscan amplifiers, with 0.1–100 Hz analog bandpass filtering and then digitized at 1000 Hz. Before performing experimental tasks, the resting-state EEGs and ECGs were recorded for 4-min under the eyes-closed condition followed by 4-min under the eyes-open condition. For these conditions, participants were told to relax in a chair and they were instructed to fixate their gaze on a central cross on a 24.4 x 18.3 cm screen located in front of them under the eyes-open condition (Gusnard and Raichle 2001). After resting-state EEG/ECG registration, each participant from the first cohort self-reported her/his condition during the resting-state recording using the Chinese version 37-item STQ (Knyazev and Slobodskaya 2003) while each participant from the second cohort filled out the 24 item BIS/BAS scale (Carver and White 1994).

HRV Analysis

Resting-state ECGs were processed separately for eyes-closed and eyes-open conditions using Kubios HRV-2.2 software (Tarvainen et al. 2014) for HRV indices in the time- and frequency-domains as well as non-linear analysis. The non-linear analysis provides measures of irregularity or complexity in an ECG time series and so are named as “non-linear” while time- and frequency-domain indices provide linear measures of HRV indices. Table 1 provides an overview of the 21 HRV indices employed in this study. Artifacts and linear trends were removed using built-in filtering and detrending functions. The signals were then examined manually for quality assurance purposes. Default HRV analysis was conducted using Welch’s periodogram method based on the Fast Fourier transform with a 60-sec window and 50% overlap, at a sampling rate of 1000 Hz and a smoothing parameter of 500 for smoothing priors in the detrending function.

The RR interval is defined as the interval from the peak of one QRS complex to the peak of the next QRS complex in an ECG time series. The time-domain indices included the SDNN, RMSSD, and pNN50 which were calculated on the basis of RR intervals. Two indices computed from the RR interval histogram were also considered. The HRV triangular index (tri_index) is the integral of the RR interval histogram (the number of RR intervals within a time series) divided by the height of the histogram (number of RR intervals in the modal bin). The triangular interpolation of RR interval histogram (TINN) is the baseline width of a triangle fitted to the histogram. All of the above time-domain indices were computed separately under eyes-closed and -open conditions (Chang et al. 2013).

Frequency domain HRV indices were computed using power spectral analysis in which the time series was transformed into the frequency domain. The RR interval time series was converted to equidistantly-sampled series via cubic spline interpolation. The HRV spectrum was calculated using the FFT-based Welch periodogram method, which involved dividing the RR time series into 60-sec time windows with 50% overlap. Spectrum estimates were obtained by averaging the FFT spectra of the windowed segments. The average spectral power was estimated within the VLF (0–0.04 Hz), LF (0.04–0.15 Hz), and HF (0.15–0.4) bands. These indices were extracted from power spectral density estimates of the RR interval time series in absolute units (ms^2). Relative power was computed by dividing the absolute power by the total spectral power. For each participant, the LF/HF ratio was computed separately under eyes-closed and eyes-open conditions by dividing the absolute power in HF and LF bands.

Several non-linear methods were also used to assess the RR time series data.

Poincaré Plots

The Poincaré plot is a simple scatter plot, which provides indices for short-term variability (SD_1) and long-term variability (SD_2), both of which are non-linearly connected to time-domain indices (Brennan, Palaniswami, and Kamen 2001). It is a graphical representation of the correlation between successive RR intervals; that is, RR_{j+1} is expressed as a function of RR_j, where RR_j denotes the R-peak at the *j*th QRS complex. The interpretation of the plot is done by parameterizing the shape so as to fit an ellipse oriented to the line of identity where $RR_{j+1} = RR_j$. The standard deviation of points perpendicular to the line of identity is denoted as SD_1. Note that this is caused primarily by respiratory sinus arrhythmia. The standard deviation of the points along the line of identity is denoted as SD_2.

Entropy

Sample entropy (SampEn) and approximate entropy (ApEn) (Richman and Moorman 2000) have been used to measure the degree of irregularity or complexity of a time series. ApEn is commonly used to quantify the entropy of a system. The derivation of ApEn involves examining a time series for similar segments and measuring the likelihood that close patterns remain close in subsequent incremental comparisons. The close patterns are defined by dividing the RR time series into a set of length *m* vectors. Here, *m* was set to a default value at 2. Note that ApEn is sensitive to the data length, which means that ApEn estimates for short time series tend to be low. SampEn is similar to ApEn; however, it does not count self-matches and is less sensitive to the data length. SampEn has been defined as the negative natural logarithm of the conditional probability that data of length N, having repeated itself within tolerance *r* for m points, will repeat itself for m+1 points. Here, m was set at 2 and *r* was set at 0.2×SDNN by default.

Detrended Fluctuation Analysis

DFA measures correlations between short-term and long-term fluctuations in an RR time series (Peng et al. 1995). The DFA algorithm proceeds through four steps: (i) removing the global mean and integrating the time series of a signal; (ii) dividing the integrated signal into non-overlapping windows of equal length n; (iii) performing least squares line fitting on each data window to obtain residuals; and (iv) detrending the integrated signal by subtracting the local trend within each segment and calculating the root-mean-square fluctuations of the integrated signal as fluctuation amplitude F(n). The same four steps are repeated for the various time scales n and plotted against window size on a log-log scale. The scaling exponent DFA α indicates the slope of the line, which relates the log of fluctuation amplitudes to the log of window sizes. Short-term fluctuations are characterized by the slope α_1 obtained from the (log (n), log F (n)) graph within the range of 4 - 12 beats, whereas long-term fluctuations are characterized by the slope α_2 obtained from the (log (n), log F (n)) graph within the range of 13 - 64 beats.

Recurrence Plot Analysis

Recurrence plot analysis (RPA) is used to visualize the recurrence behavior of a phase space trajectory in dynamic systems (Marwan et al. 2007). A phase space trajectory is first reconstructed from a time series using time delay embedding m. Close states in the phase space can then be plotted as a recurrence plot in accordance with threshold *r*. A recurrence plot is a symmetrical matrix of zeros and ones with order $[N - (m - 1)\tau]$ by $[N - (m - 1)\tau]$, where m is the embedding dimension and τ is the embedding lag. In the current study, we used the following settings: m = 10, $\tau = 1$, and r = $\sqrt{m}$ × SDNN. Recurrence quantification analysis was used to define measures for diagonal segments in a recurrence plot, which includes the following: (i) the recurrence rate (RPA_REC) indicating the recurrence probability measured as the percent of the plot filled with recurrent points, (ii) determinism (RPA_DET) indicating the degree of predictability measured by the percent of recurrent points forming diagonal lines with a minimum of two adjacent points, (iii) the Shannon entropy of line length distribution (RPA_ShanEn), and (iv) the maximum line length (l_{max}) which is inversely related to the largest positive Lyapunov exponent as a measure of system divergence (RPA_DIV).

Other Information Measures

The correlation dimension (CorDim) index (Grassberger and Procaccia 1983) is another measure of signal complexity, which provides information pertaining to the minimum number of dynamic variables required to model the underlying system.

Table 1. Overview of the HRV indices considered in this study

Indices	Units	Definitions
SDNN	[sec]	The standard deviation of RR intervals.
RMSSD	[sec]	The square root of the mean squared differences between successive RR intervals.

pNN50	[%]	The number of successive RR interval pairs that differ more than 50 ms divided by the total number of RR intervals.
HRV_tri_index		The integral of the RR interval histogram divided by the height of the histogram.
TINN		Baseline width of the RR interval histogram.
HF_power_prc	[%]	HF[%] = HF[ms^2] / total power[ms^2] × 100%
LF_power_prc	[%]	LF[%] = LF[ms^2] / total power[ms^2] × 100%
VLF_power_prc	[%]	VLF[%] = VLF[ms^2] / total power[ms^2] × 100%
LF/HF		The ratio between LF and HF powers.
Poincare_SD$_1$	[ms]	Poincare plot for short term variability.
Poincare_SD$_2$	[ms]	Poincare plot for long term variability.
ApEn		Approximate entropy.
SampEn		Sample entropy.
CorDim		Correlation dimension.
DFA_α_1		Detrended fluctuation analysis: Short term fluctuation slope.
DFA_α_2		Detrended fluctuation analysis: Long term fluctuation slope.
RPA_Lmean	[beats]	Recurrence plot analysis: Mean line length.
RPA_DIV		Recurrence plot analysis: Divergence.
RPA_REC	[%]	Recurrence plot analysis: Recurrence rate.
RPA_DET	[%]	Recurrence plot analysis: Determinism.
RPA_ShanEn		Recurrence plot analysis: Shannon entropy.

Principal Component Analysis

Principal component analysis (PCA) is a multivariate statistical procedure with which random observations are transformed into a smaller set of uncorrelated variables referred to as principal components (PCs) (Jolliffe 2014). In other words, the original variables are presented as a weighted sum of orthogonal basis vectors, where the basis vectors are the eigenvectors of the data correlation (or covariance) matrix and the weights are the PCs. Typical applications of PCA include dimension reduction, feature extraction, and visualization of multidimensional data. In this chapter, PCA was used to analyze the correlation matrix among HRV indices in order to interpret multidimensional HRV data in reduced dimensions. The PCA results for 42 HRV indices (under eyes-closed and eyes-open conditions with 21 indices each) generated 9 components following PCA feature extraction (Tabachnick, Fidell, and Ullman 2019). After orthogonal varimax rotation of the 9 PCs, the time-domain HRV indices and Poincare plot analysis indices were neatly loaded on the same dimension, whereas the frequency-domain, non-linear, and VLF indices were loaded on separate dimensions depending on the resting-state conditions, that is, eyes-closed (EC) or eyes-open (EO) conditions. The 9 factors explained 87% of the overall data variance. The $ApEn^{EO}$ and RPA_Lmean^{EC} indices in Table 1 measured two PCs, which were uncorrelated with other HRV indices. $ApEn^{EC}$ had a higher loading on the dimension represented by the VLF power and DFA_α_2 while RPA_Lmean^{EO} had higher loading on the non-linear HRV dimension under the eyes-open condition. For ease of interpretation, we eliminated those 4 indices (i.e., $ApEn^{EC}$, $ApEn^{EO}$, RPA_Lmean^{EC}, and RPA_Lmean^{EO}), and re-conducted PCA on the remaining indices. The time-domain indices were robust to eyes-closed and eyes-open conditions; therefore, the 8-min time-domain HRV indices were estimated again by combining the ECGs obtained under the two resting-state conditions. The resulting PCA suggested 7 components, which accounted for 85.34% of the variation among the 31 indices. The component scores were estimated for individual participants using the regression method (Tabachnick, Fidell, and Ullman 2019). PCA, varimax rotation, and estimation of component scores were conducted using IBM SPSS Statistics 20.

Statistical Analysis

To establish a link between latent HRV dimensions and STQ, cSTAI, and BIS/BAS behavioral scores, we ran a series of stepwise regressions to facilitate the selection of variables using the SPSS package.

RESULTS

Among the 31 selected HRV indices as listed in Table 2, those in the frequency-domain differed significantly in terms of gender, wherein the average HF index of women was higher than that of men ($p < .001$ under both resting-state conditions), and women had the lower average LF index ($p < .001$ under both resting-state conditions) and lower average LF/HF ratio ($p < .001$ under the eyes-closed condition and $p = .003$ under the eyes-open condition) (Koenig and Thayer 2016). It is widely known that DFA_α_1 can be estimated by LF/(LF+HF) (Francis et al. 2002); therefore, it is not surprising that this HRV index also revealed significant gender differences, wherein the α_1 values of men were higher than those of women under both resting-state conditions (Voss et al. 2015). The pNN50 index was the only time-domain index that presented significant differences between genders (Voss et al. 2015). Generally, the time-domain HRV indices were higher in women than in men. Men and women presented comparable mean values on non-linear indices under eyes-closed as well as eyes-open conditions, a case which indicates that non-linear HRV indices may be insensitive to gender differences. Under the eyes-open condition, the VLF and DFA_α_2 indices of men and women were comparable. However, the VLF and DFA_α_2 indices of men tended to be higher under the eyes-closed condition. Also, the CorDim indices of women were slightly higher than those of men under both resting-state conditions. After controlling for gender differences, all time-domain indices were significantly correlated with ages, wherein the time-domain indices of older participants tended to be lower (e.g., Poincare_SD_1 and Poincare_SD_2). After controlling for the gender differences, the other HRV indices appeared to be uncorrelated with ages. In summary, the HRV levels of women tended to be higher than those of men (particularly under the resting-state eyes-closed condition), and time-domain indices were sensitive to age differences. Non-linear HRV indices were relatively unaffected by age and gender differences; therefore, we explored their use as covariates in predicting cognitive outcomes.

Table 2. Statistical t-test for gender and age effects

PCs	HRV indices	Men	Women	Age[a]
Time	SDNN [8-min]	.058 (.023)[b]	.060 (.026)	-.292**
	pNN50 [8-min]	25.559 (17.747)	33.419* (17.624)	-.252*

	TINN [8-min]	.394 (.165)	.450 (.251)	-.311**
	RMSSD [8-min]	.059 (.030)	.070 (.038)	-.328**
	HRV_tri_index [8-min]	12.703 (4.184)	13.143 (4.197)	-.308**
	Poincare_SD_1 [8-min]	.042 (.021)	.050 (.027)	-.328**
	Poincare_SD_2 [8-min]	.070 (.026)	.067 (.027)	-.255*
$Freq^{EC}$	HF_power_prc^{EC}	42.501 (19.160)	62.403** (15.719)	-.071
	LF_power_prc^{EC}	51.112 (17.754)	33.355** (14.462)	.070
	LF/HF_$power^{EC}$	1.747 (1.406)	.629** (.401)	.055
	DFA_$\alpha_1{}^{EC}$	1.020 (.282)	.773** (.229)	.089
$Freq^{EO}$	HF_power_prc^{EO}	40.087 (17.351)	54.237** (17.559)	-.106
	LF_power_prc^{EO}	53.134 (15.804)	39.905** (16.123)	.122
	LF/HF_$power^{EO}$	1.932 (1.857)	.992** (.888)	.169
	DFA_$\alpha_1{}^{EO}$	1.065 (.275)	.874** (.244)	.209
$Nonlin^{EC}$	$SampEn^{EC}$	1.592 (.324)	1.550 (.302)	.038

Table 2. (Continued)

PCs	HRV indices	Men	Women	Age^a
	RPA_DET^{EC}	.972 (.016)	.969 (.016)	-.097
	RPA_DIV^{EC}	.014 (.007)	.015 (.007)	.027
	RPA_REC^{EC}	.297 (.136)	.294 (.155)	-.078
	RPA_$ShanEn^{EC}$	3.014 (.431)	3.033 (.358)	-.081
$Nonlin^{EO}$	$SampEn^{EO}$	1.526 (.340)	1.551 (.269)	-.043
	RPA_DET^{EO}	.974 (.017)	.976 (.014)	-.034
	RPA_DIV^{EO}	.012	.013	-.091

		(.007)	(.006)	
	RPA_REC^{EO}	.331 (.171)	.342 (.159)	.005
	RPA_ShanEn^{EO}	3.048 (.401)	3.111 (.343)	-.008
VLF	VLF_power_prc^{EC}	6.290 (5.088)	4.140* (3.017)	.027
	VLF_power_prc^{EO}	6.677 (4.253)	5.753 (3.494)	-.020
	DFA_α_2^{EC}	.305 (.135)	.291 (.121)	.024
	DFA_α_2^{EO}	.347 (.142)	.351 (.108)	-.178
CorDim	CorDim^{EC}	2.893 (1.208)	3.087 (1.101)	-.124
	CorDim^{EO}	2.916 (1.155)	3.144 (.940)	-.090

[a] The partial correlations between age and HRV indices conditional on the gender effect. [b] The standard deviation of each HRV index listed in parentheses. The symbol "*" indicates that the two-sample t-test or partial correlation is significant at p < .05, and the symbol "**" indicates that the test is significant at p < .01.

As shown in Table 3, the latent dimension referred to as *Time* had positive loadings on all 8-min time-domain indices. The two latent dimensions, so-called $Freq^{EC}$ and $Freq^{EO}$ respectively, had high loadings on indices in the frequency-domain; however, HF indices had negative loadings on these dimensions and the other indices had positive loadings. As mentioned, DFA_α_1 can be approximated by LF/(LF+HF) (Francis et al. 2002). Thus, the only difference between LF/HF and LF/(LF+HF) is the denominator. We may interpret $Freq^{EC}$ and $Freq^{EO}$ as HRV dimensions reflecting a balance between sympathetic and parasympathetic activity. The two non-linear dimensions referred to as $Nonlin^{EC}$ and $Nonlin^{EO}$ respectively had high loadings on non-linear indices; however, SampEn and RPA_DET had negative loadings and the other indices had positive loadings on these dimensions. One study reported that the SampEn index had a negative loading on the non-linear HRV dimension (Young and Benton 2015), whereas the RPA_DET index had a positive loading on the non-linear HRV dimension. The ECG recordings in Young and Benton's study were obtained while the participants were relaxing and listening to calming music for 5-

min. In the current study, ECG recordings were obtained with the participants in a resting state under eyes-closed or eyes-open conditions. It is possible that the difference between the findings in the two studies can be attributed to the presence/absence of calming music (Young and Benton 2015). It has previously been demonstrated that DFA_α_2 is mathematically associated with the VLF index, which means that it can be approximated by VLF/(VLF+LF) (Francis et al. 2002). The so-called *VLF* dimension is primarily a reflection of the long-memory component in DFA. The two correlation dimension indices measured a single dimension, *CorDim*. We did not combine the two indices into a single 8-min CorDim index because the correlation between the two indices was deemed insufficient (despite reaching statistical significance) ($r = 0.68$; $p < .001$).

Among the 7 HRV dimensions listed in Table 4, $Freq^{EC}$ and $Freq^{EO}$ showed significant gender-related differences; that is, the component scores of women on these dimensions were significantly lower than those of men. There were insignificant correlations between age and all component scores except for *Time*, a case which suggested that the component scores gained by younger participants during the ECG recording were higher than those of their older counterparts. The statistical test results pertaining to component scores were consistent with the indices in Table 2. In other words, the 7 latent dimensions preserved the important gender-related and age-related information in the original raw indices. In summary, the two latent dimensions related to HRV indices in the frequency-domain were sensitive to gender differences, whereas the dimension related to the time-domain indices was sensitive to age differences. Other latent dimensions were relatively independent of gender and age effects. Nonetheless, none of the subscale scores on the STQ (drowsiness, emotion, ATT, or SRT) presented significant differences between genders, and when the gender effect was eliminated, none of the correlations between ages and subscale scores reached the level of significance. Furthermore, none of the BIS scores or subscale scores on the BAS scale (drive, fun-seeking, or reward responsiveness) presented significant gender differences, and none of the partial correlations between ages and those BIS/BAS scores reached the level of significance. The state- and trait-anxiety scores of women were slightly higher than those of men, but none of those differences reached the level of statistical significance.

Table 3. Latent dimensions of 31 HRV indices after the varimax rotation

HRV	Time	Freq^{EO}	Nonlin^{EC}	Nonlin^{EO}	Freq^{EC}	VLF	CorDim
SDNN (8-min)	**.970**	-.007	.112	.140	-.006	-.019	.088
HRV_tri_index (8-min)	**.681**	-.257	-.226	-.308	-.287	-.169	.190
pNN50 (8-min)	**.758**	-.149	.146	.482	.058	.055	.021
TINN (8-min)	**.914**	-.269	.076	.093	-.128	-.064	-.007
RMSSD (8-min)	**.858**	.071	-.044	-.230	-.078	-.160	.163
Poincare_SD_1 (8-min)	**.914**	-.269	.076	.093	-.128	-.064	-.007
Poincare_SD_2 (8-min)	**.928**	.148	.119	.160	.064	.015	.146
HF_power^{EC} (4-min)	.078	-.330	-.119	-.161	**-.885**	-.178	.010
LF_power^{EC} (4-min)	-.063	.362	.130	.177	**.870**	.001	-.032
LF/HF_ratio^{EC} (4-min)	-.032	.385	.197	.053	**.798**	.030	-.045
DFA_α_1^{EC} (4-min)	-.190	.463	.116	.212	**.703**	.174	-.090
HF_power^{EO} (4-min)	.050	**-.877**	.102	-.081	-.290	-.205	.060
LF_power^{EO} (4-min)	-.057	**.861**	-.114	.079	.328	.055	-.024
LF/HF_ratio^{EO} (4-min)	-.079	**.837**	.081	.041	.253	-.078	-.021
DFA_α_1^{EO} (4-min)	-.238	**.853**	.015	.132	.291	.114	-.011

Table 3. (Continued)

HRV	Time	Freq^{EO}	Nonlin^{EC}	Nonlin^{EO}	Freq^{EC}	VLF	CorDim
SampEn^{EC} (4-min)	-.077	-.008	**-.858**	-.228	.049	.215	.015
RPA_DIV^{EC} (4-min)	.115	.042	**.895**	.242	.154	.096	-.031
RPA_DET^{EC} (4-min)	.161	-.070	**-.816**	-.045	-.185	-.089	.240
RPA_ShanEn^{EC} (4-min)	.190	-.114	**.731**	.392	.155	.222	.045
RPA_REC^{EC} (4-min)	.080	-.134	**.817**	.295	.066	.150	-.037
SampEn^{EO} (4-min)	-.245	-.236	-.511	**-.638**	-.125	-.001	.132
RPA_DIV^{EO} (4-min)	.123	.217	.322	**.827**	.128	.050	-.089
RPA_DET^{EO} (4-min)	.178	-.393	-.134	**-.664**	-.153	-.030	.062
RPA_ShanEn^{EO} (4-min)	.169	-.039	.205	**.889**	.115	.161	-.104
RPA_REC^{EO} (4-min)	.038	-.038	.327	**.855**	.086	.086	-.071
VLF_power^{EC} (4-min)	-.099	-.004	-.010	-.007	.403	**.810**	.087
VLF_power^{EO} (4-min)	.006	.424	.013	.035	-.056	**.730**	-.182
DFA_α_2^{EC} (4-min)	-.248	-.143	.126	.108	.192	**.736**	.044
DFA_α_2^{EO} (4-min)	.045	.204	.125	.224	-.197	**.741**	-.283

$CorDim^{EC}$ (4-min)	.355	-.083	-.165	-.142	.011	-.184	**.772**
$CorDim^{EO}$ (4-min)	.096	-.024	-.076	-.124	-.099	-.027	**.916**

Table 4. Statistical t-test for gender and age effects on the the 7 HRV component scores

PCs	Men	Women	Age[a]
Time	-.022 (.889)	.027 (1.132)	-.328**
$Freq^{EC}$	.422 (.947)	-.520** (.807)	.041
$Freq^{EO}$	.226 (1.056)	-.278** (.859)	.098
$Nonlin^{EC}$	<.001 (.954)	< - .001 (1.065)	-.059
$Nonlin^{EO}$	-.123 (1.009)	.152 (.980)	.052
VLF	.048 (1.154)	-.059 (.778)	-.102
CorDim	-.067 (1.080)	.082 (.897)	-.016

[a] The partial correlations between age and component scores conditional on the gender effect. The symbol "*" indicates that the two sample t-test or partial correlation is significant at $p < .05$, and the symbol "**" indicates that the test is significant at $p < .01$. The means and standard deviations of component scores are listed in the table according to genders and HRV dimensions.

Table 5. Stepwise regression analysis on the HRV component scores and psychological scale scores

Scale scores	Age	Gender	Time	$Freq^{EC}$	$Freq^{EO}$	$Nonlin^{EC}$	$Nonlin^{EO}$	VLF	CorDim
Self-Referential Thought (N = 57)									
Emotions							t_{54} = -2.498; p= .016		t_{54} = 2.857; p= .006
SRT		t_{54} = 2.103; p= .040		t_{54} = 3.316; p= .002					
ATT						t_{54} = -2.071; p= .043	t_{54} = 2.332; p= .023		
Drowsiness			t_{53} = -3.341; p= .002		t_{53} = -1.776; p= .081	t_{53} = 2.167; p= .035			

BIS/BAS Scales (N = 39)										
BIS		t_{36} = 1.777; *p*= .084				t_{36} = -3.162; *p*= .003				
BAS_Drive										
BAS_FunSeeking										
BAS_reward										
State-Trait Anxiety (N = 96)										
Trait Anxiety						t_{94} = -1.876; *p*= .064				
State Anxiety	t_{92} = -2.674; *p*= .009					t_{92} = -2.356; *p*= .021	t_{92} = -1.912; *p*= .059			

Table 5 lists the HRV dimensions that had significant effects in predicting the scores on different psychological scales under stepwise regression analysis. To compensate for the small sample sizes, we opted for the inclusion of predictors in the stepwise procedure using the critical value $\alpha = 0.09$ (rather than 0.05). For example, *Nonlin*^{EO} and *CorDim* appeared to have significant effects when used to predict emotion scores in the STQ following the inclusion of age, gender, and all 7 of the HRV dimensions within the regression model. The *Nonlin*^{EO} dimension was negatively correlated with pNN50 (r = -.308; p = .002) and HRV_tri_index (r = -.230; p = .024); however, it was positively correlated with TINN (r = .482; p < .001) and DFA_α_1 (r = .212; p = .038). Our regression results suggest that participants presenting signs of positive emotions during the ECG recording tended to achieve lower *Nonlin*^{EO} scores (r = -.310, p = .019). Nonetheless, emotion scores were uncorrelated with *Nonlin*^{EC} scores (r = .002, p = .987). It is interesting to note that *CorDim* was not correlated with any of the HRV indices in the time- or frequency-domain. Furthermore, participants presenting signs of positive emotions during the ECG recording tended to achieve higher *CorDim* scores (r = .352, p = .007), which could conceivably be interpreted as a positive emotion index. The regression results also suggest that gender and *Freq*^{EC} were significant predictors of SRT scores. The *Freq*^{EC} dimension was negatively correlated with pNN50 (r = -.287; p = .005) given that this component had a negative correlation with the HF power and a positive correlation with the LF power. Thus, *Freq*^{EC} scores could be considered an indicator of sympathetic activity. As mentioned, a lower SRT score is an indication that the participant was more able to recall events in his or her daily life. Our regression results suggest that men under parasympathetic control would tend to recall daily life events during the ECG recording.

The *Nonlin*^{EC} dimension was negatively correlated with pNN50 (r = -.226; p = .027) and uncorrelated with other indices in the time- and frequency-domains. This dimension was strongly associated with the degree of attention paid by participants to odors, sounds, and skin sensations during the recordings. Participants with lower *Nonlin*^{EO} scores (positive emotions) and higher *Nonlin*^{EC} scores tended to pay attention to the recording procedure. It is interesting to note that higher *Nonlin*^{EC} scores were also associated with less pronounced social withdrawal on the BIS (r = -.465; p = .003). It would be reasonable to hypothesize that the *Nonlin*^{EC} dimension could be used as a social withdrawal index, reflecting the degree of attention paid to the recording procedure, where a higher *Nonlin*^{EC} score was associated with more attention and less pronounced social withdrawal. Drowsiness (based on arousal scores) had significantly negative correlations with all indices in the time domain. In other words, the level of arousal in participants was proportional to the degree to which they were under sympathetic control and the level of attention they paid to ECG recording procedures (i.e., odors, sounds, and skin sensations). Note that the function of *Freq*^{EO} scores was similar to that of *Time* scores. The results in Table 5 suggest that the BIS scores were strongly associated with gender and *Nonlin*^{EC}. Women had higher BIS scores and paid less attention to ECG recording procedures, compared with men. Younger participants also had higher state-anxiety scores and appeared to pay more attention to the ECG recording procedures. The *VLF* dimension was not strongly predictive of scale scores in the current study; however, it may be a predictor of other behavioral outcomes.

DISCUSSION

In this chapter, our analysis revealed an association between various psychological scales and the latent structures of short-term HRV indices under two resting-state conditions. We also explored the effects of gender, age, and resting-state condition on these latent structures. Frequency-domain and non-linear HRV indices could be used to differentiate eyes-closed and eyes-open conditions, as evidenced by our PCA results. Thus, we strongly recommend that indices in the time-domain be used to index short-term resting-state ECGs in cases where resting-state conditions are not an issue of primary concern. The indices in the time- and frequency-domains revealed that parasympathetic activity is more pronounced in women than in men. The time-domain indices also revealed that older participants were more profoundly affected by sympathetic activity than were their younger counterparts. This is the first study to characterize physiological and affective status during the resting-state ECG recording based on latent HRV dimensions. Our stepwise regression analysis suggested the following: (i) the latent dimension *Time* was a good indicator of drowsiness in participants; (ii) $Freq^{EC}$ was strongly associated with SRT scores and a reliable indicator of sympathetic activity; (iii) $Nonlin^{EC}$ was strongly associated with anxiety and social withdrawal and was a reliable predictor of drowsiness and the degree of attention paid to the ECG recording procedure; (iv) $Nonlin^{EO}$ was strongly associated with the emotional experience of participants during the recording process as well as the degree of attention to the ECG recording procedure; (v) *CorDim* was significantly correlated with positive emotions during the ECG recording.

Our analysis results suggested that $Nonlin^{EC}$ and $Nonlin^{EO}$ were relatively robust to gender and age differences in young adults. Previous studies have recommended using non-linear HRV indices to predict gender-by-behavior interactions in terms of attention, memory, reaction times, emotional responses, and cortisol levels (Young and Benton 2015). It was reported that the use of non-linear HRV indices could significantly increase the percentage of variation explained in regression analysis for the prediction of behavioral outcomes. For example, frequency-domain indices alone were unable to predict treatment outcomes in patients who were afraid of flying, but the predictive power was increased by 18% after adding the SampEn index to the regression model (Bornas et al. 2006). It was also reported that non-linear HRV indices were significantly related to ratings of depression and salivary cortisol levels, whereas frequency- and time-domain indices were associated with perceived stress and anxiety (Young and Benton 2015). Those researchers suggested that non-linear HRV indices capture additional information on top of those obtained based on traditional HRV indices. They also indicated that in some instances, the contribution of non-linear HRV indices was essential to predictive performance (e.g., *CorDim* and $Nonlin^{EC}$). It is interesting to note that $Nonlin^{EC}$ and $Nonlin^{EO}$ predicted ATT scores well as indicated in the results in Table 5. However, if we considered the 10 raw non-linear indices in the stepwise regression, none of these indices would have a significant effect in predicting the ATT scores at $\alpha = 0.09$. This finding has demonstrated that latent dimensions of HRV indices are more predictive of psychological traits than are the original non-linear indices.

The psychophysiological underpinnings of non-linear HRV have yet to be investigated; however, there is rich evidence indicating that these indices could be used to quantify heart rate dynamics and have a strong association with the functioning of the central nervous system. Previous studies used pharmacological intervention to clarify the contribution of activity in the autonomic nervous system (ANS) to measures of complexity in characterizing HRs. For example, one study measured linear (SDNN, RMSSD, LF power, and HF power) and non-linear (short-term DFA_α_1 and ApEn) HRV indices for a 5-min period before and after the intravenous injection of 0.6 mg of atropine (a parasympathetic antagonist). The results in that study revealed a significant increase in DFA_α_1 after atropine injection (Perkiomaki et al. 2002). In addition, DFA_α_1 showed significant negative correlations with several linear HRV indices (SDNN, RMSSD, and HF power) and a positive correlation with HRs at the baseline level while this effect vanished after atropine injection. Interestingly, ApEn failed to show significant correlation with any of the linear HRV indices or HR either before or after the atropine treatment. This suggests that vagal activity has a significant contribution to the fractal nature of HR time series, but it is not a major determinant of ApEn. Our study has partially supported this notion. Specifically, PCA revealed that DFA_α_1 was loaded heavily on the same dimensions as were indices in the frequency domain; however, SampEn and the recurrent plot indices co-loaded onto a separate dimension (Young and Benton 2015) under the eyes-closed condition or eyes-open condition, respectively. We recommend measuring HR entropy and performing RP analyses since they are both able to capture information that is not attributable to ANS activity as reflected by linear HRV indices in time- and frequency-domains.

To the best of our knowledge, this is the first study to use resting-state HRV indices for the prediction of STQ scores. Previous research linked the DFA_α_1 index with anxiety scores and affective problems (Fiskum et al. 2018). By contrast, our findings indicated that SRT scores could be predicted based on $Freq^{EC}$ (including DFA_α_1). Drowsiness has traditionally been associated with the parasympathetic nervous system. Research showed that the HR decreased with sleepiness in drivers, leading to increases in HRV based on the SDNN, TINN, and Poincare SD_1, SD_2 indices (Buendia et al. 2019). By contrast, we found that *Time* was a significant predictor of "drowsiness." One previous study reported that non-linear HRV indices could increase the predictive power of a regression model used to account for reaction times obtained from focused attention tasks (Young and Benton 2015). This suggests that $Nonlin^{EO}$ may play a general role in attention status. In line with this finding, we demonstrated that $Nonlin^{EO}$ was positively predictive of ATT scores and negatively predictive of emotion scores.

In the current study, BIS scores were negatively correlated with $Nonlin^{EC}$ component scores ($r = -.465$, $p = .003$) and positively correlated with trait-anxiety scores ($r = .781$, $p < .001$). These findings are consistent with recent reports characterizing the relationship between anxiety and non-linear HRV. The BIS is a complex system involving the inhibition of ongoing behaviors, increasing vigilance, and promoting arousal in reaction to stimuli associated with pain, punishment, failure, loss of reward, novelty, or uncertainty (Gray 1982). Trait-anxiety is closely related to sensitivity toward BIS activation (Corr and Cooper 2016). Thus, individuals with high trait-anxiety tend to receive higher scores on the BIS scale. It was previously demonstrated that BIS scores were associated with alpha power under resting-state conditions (Knyazev, Savostyanov, and Levin 2004; Knyazev and Slobodskaya 2003), and that the BIS and anxiety scores of women were higher than those of men. One recent study reported a significant correlation between state anxiety and SampEn (Dimitriev, Saperova, and Dimitriev 2016) during rest and exam sessions as well as a significant correlation between state anxiety and DFA_α_2 during exam sessions. Another study using RMSSD as an indicator of parasympathetic control found no correlation between HRV and BIS scores (Scholten et al. 2006). Despite a small sample size, our study showed that BIS could be predicted by $Nonlin^{EC}$, suggesting that non-linear HRV indices revealed information beyond the ANS. Previous study showed strong correlations between BIS scores and scores on negative affectivity scales and neuroticism (Jorm et al. 1998). In contrast, weak correlations were reported between BIS scores and symptoms of anxiety and depression. This can be explained by the fact that BIS scores have been designed to measure one's predisposition to anxiety rather than the experience of anxiety. The fact that gender ($t_{36} = 2.286$; $p = .028$) and trait-anxiety scores ($t_{36} = 4.882$; $p < .001$) were strongly predictive of BIS scores (Table 5) means that trait-anxiety remains the best predictor of BIS, which is also strongly associated with $Nonlin^{EC}$.

Broadly speaking, our results are indicative of two separate dimensions within the sympathetic domain. Specifically, HRV indices classified to $Freq^{EC}$, $Freq^{EO}$, $Nonlin^{EC}$, and $Nonlin^{EC}$ were negatively correlated with HF, RMSSD, SDNN and pNN50. We could argue that *Time* was a measure of parasympathetic activity owing to positive loadings of RMSSD, SDNN and pNN50 on this dimension. Since $Freq^{EC}$, $Freq^{EO}$, $Nonlin^{EC}$, and $Nonlin^{EC}$ were negatively correlated with the above mentioned indices measuring parasympathetic activity, we could further argue that they might be measuring activity in the sympathetic domain. This distinction is most notable in $Nonlin^{EC}$, and $Nonlin^{EO}$, wherein eyes-closed and eyes-open conditions differed (positive and negative t values in Table 5) in their predictions of "attention to the ECG recording procedure." Note that state-anxiety scores were negatively predicted by both *Nonlin*^{EC} and *Nonlin*^{EO}; that is, lower state anxiety scores were associated with higher *Nonlin*^{EC} and *Nonlin*^{EO} component scores. This means that state anxiety could not be used to differentiate between eyes-closed and eyes-open conditions in non-linear HRV dimensions. This distinction is yet to be accounted for in future studies on individual differences and personality traits. We were unable to find well-documented instances of gender differences pertaining to the BIS/BAS scales. Note that a relatively small sample in this study might have prevented our detection of more significant gender differences in BIS/BAS. Age had a significant effect on state-anxiety, but not on any STQ subscale. Future studies would no doubt benefit from a larger sample size with a greater age range.

In conclusion, the non-linearity of many biological processes (e.g., HRV and brain functioning) (Mattei 2014) means that linear indices must be combined with non-linear indices for the prediction of complex behaviors. The present study found that non-linear HRV indices were independently predictive of several physiological and affective states under resting-state conditions. In such cases, conventional HRV indices in the time- and frequency-domains lacked any predictive ability. In the future, researchers should consider the influence of the HPA axis on the modulation of HRV indices, and particularly on indices pertaining to heart rate entropy and recurrence quantification analysis. We recommend collecting data pertaining to cortisol levels and sex-hormones when replicating our experiment using other stress-related tasks.

ACKNOWLEDGEMENT

This research was supported by grants MOST-106-2410-H-001-026 and MOST-106-2420-H-001-006-MY2 from the Ministry of Science and Technology, Taiwan.

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