DETERMININING CLINICALLY RELEVANT MEASURES FOR EVALUATING RECOVERY IN COLLEGIATE ATHLETES USING HEART RATE VARIABILITY AND THE RESTQ-SPORT

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Abstract

Introduction: Effective training involves the accumulation physical stresses in an effort to produce overload and effect physiological change. The ability to quantify the balance of training stress and recovery on an individual basis is lacking, as is the ability to identify athletes who are not fully recovered in order to make changes earlier in their training. Evaluating recovery on a regular basis has the advantage of indicating an increased need for rest prior to performance declines allowing the athlete to resume normal training and competition following a brief respite. The method of collecting this data should be easy and readily available to the athlete, be validated against existing methods and allow for changes that are clinically relevant even if they are not statistically significant. Four separate studies were used to evaluate recovery methods in Collegiate Student athletes using subjective and objective measures.

Methods: Heart rate variability was assessed using traditional ECG methods of data collection as well as with photoplethysmography using the flash form a smartphone and a smartphone application. Subjective stress levels were assessed using the RESTQ-Sport and evaluation of training load, the product of minutes trained times RPE.

Conclusions: While time domain and frequency domain measures cannot be used interchangeably, the HF power of AR is an acceptable alternative to RMSSD, the preferred time domain measure. There is a clear curvilinear relationship between HRV measures and stress in collegiate athlete however there is not one measure that best associates to any one RESTQ-Sport scale. The use of a smartphone application is acceptable for evaluating the time domain measures of HRV but not the frequency domain measures as the application uses different methods of calculation. The RR intervals obtained from the smartphone can be assessed using Kubios HRV software in order to determine HRV measures. The SRM is an appropriate

statistical measure for evaluating change in daily HRV measures for collegiate football players. The 0.5 SD of change appears too conservative of a measure to evaluate change and a 90% CI is more appropriate, especially in athletes who primarily undergo anaerobic training.

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List of Abbreviations

- HRV – Heart Rate Variability
- RMSSD – Root Mean Squares of Standard Deviation of R-R Intervals
- SDNN – Standard Deviation of the Normal-Normal Intervals
- SDANN – Standard Deviation of the average Normal-Normal Intervals
- LF – Low Frequency
- HF – High Frequency
- nu – normalized units
- VLF – very low frequency
- FFT – Fast Fourier Transformation
- ANS – Autonomic Nervous System
- ECG – electrocardiographic
- PPG – photoplethysmography
- PRV – pulse rate variability
- HR – heart rate
- BP – blood pressure
- SD – standard deviation
- LNRMSSD – log of the root mean squares of the standard deviation of R-R intervals
- SWC – Smallest Worthwhile Change
- RCI – reliable change index
- SRM – standardized response mean
- RS – responsiveness statistic
- NCAA – National Collegiate Athletic Association
- RPE – Rating of Perceived Exertion
- NN – normal-to-normal intervals
- AR – Autoregressive analysis
- TP – total power
- SA node – sinoatrial node
- RESTQ-Sport – Recovery-Stress Questionnaire for Athletes
- OTS – overtraining syndrome
- AV node – atrioventricular node

- PTT – pulse transit time
- PPI – pulse to pulse interval
- RRI – R to R interval
- pNN50 – percentage or proportion of N-N intervals above 50
- HRR – heart rate recovery
- CV – coefficient of variation
- RHR – resting heart rate
- NFOR – non-functional overreaching
- FOR – functional overreaching
- BMI – body mass index
- AcH – acetylcholine
- POMS – Profile of Mood States
- OT – overtraining
- PDTL – Previous Day's Training Load

Chapter 1

Comparing the Frequency Domain measures of fast Fourier Transformation and Autoregressive Analysis in NCAA Division I Collegiate athletes

INTRODUCTION

The parasympathetic and sympathetic pathways of the autonomic nervous system (ANS) regulate heart rate variability (HRV), modulation of the interbeat intervals and the oscillations between consecutive instantaneous heartbeats [1-4]. Because the sympathetic and parasympathetic nervous systems have differing response characteristics on HR modulations, analysis of HRV is used to determine how the systems regulate sympathovagal balance [2]. Analysis of HRV is done through the examination of electrocardiographic (ECG) recordings of the intervals between the peaks of successive QRS complexes (R-R intervals) using time domain and frequency domain measures [1, 3]. Time domain measures use statistical analyses involving the standard deviation of the rate between successive normal-to-normal (NN) intervals such as the square root of the mean squared difference of those intervals (RMSSD) to reflect variance, the mathematical equivalent of power [1, 5-9]. Frequency domain measures are a function of how power (variance) distributes as a function of frequency, and are expressed in absolute values of power (m^2) or normalized units (nu) where the influence of the thermoregulatory effect is removed from the absolute value [1]. In this measure the patterns of oscillation divide the spectral components of HRV into bands, very low frequency (VLF) influenced by thermoregulatory effects, low frequency (LF) under influence of the sympathetic and parasympathetic systems, and high frequency (HF) modulated by the parasympathetic nervous system [1, 2, 10]. The sympathetic tone reflected in LF is hypothesized to come from vaso- and thermoregulatory mechanisms while the variations in HF occur during normal respiration from increased parasympathetic activity with expiration and inhibited activity during inspiration [10, 11]. The LF/HF ratio is then used as a reflection of the sympathovagal balance [1, 2]. Time and frequency domain measures do have a high degree of multicollinearity however they do not allow for direct comparisons and caution must be used if measures are taken under differing methodologies as variations in positioning and length of recording time lead to differing results [1, 4, 12].

Frequency domain measurements can be expressed in either non-parametric fast Fourier transformation (FFT) or parametric autoregressive (AR) analysis [1]. In FFT the RR interval series are decomposed into a spectrum of sinusoidal components where LF and HF are estimated into specific ranges [13]. The FFT method employs a simple algorithm and a high processing speed, and has the advantage of good reproducibility however there is often an overlap in the bands that increase the values of the LF and HF power, placing LF measures in HF bands and HF measures in LF bands, potentially overestimating the parasympathetic modulations during HRV analysis [1, 14, 15]. The parametric AR method fits the RR interval series into an AR model and estimates the spectrum from the model parameters giving it a smoother spectral component making it easier to distinguish peaks between the HF and LF components in order to identify the central frequency of the spectra [13]. At low breathing frequencies the peaks broaden increasing the overlap between HF and LF preventing a clear separation into components thereby increasing the LF/HF ratio resulting in an increased value for sympathetic activity as well as overestimating the parasympathetic modulation, however this is only if AR is used during methodologies involving paced respiration. [1, 13, 14, 16] In direct comparison of the two techniques, active individuals at rest had a significantly higher total power (TP) and HF absolute power using FFT analysis compared to AR while during recovery from exercise the same individuals continued to have a higher HF absolute power in FFT but also yielded a higher

LF/HF in AR which was different from what was found at rest [17]. While there is often a strong correlation between the two methods, a Bland-Altman plot revealed a large discrepancy for all the frequency domain indices at rest and during orthostatic testing confirming that the measures are different [15]. The FFT and AR analyses cannot be used interchangeably or compared directly and there is no consensus as to which is the appropriate method of analysis for athletes [14-17].

Time domain measures are the preferred measure for evaluating athletes as the saturation of the sino-atrial (SA) node by acetylcholine (AcH) can distort the frequency domain measures in individuals with a resting heart rate below 60 beats per minute [7, 8, 18]. With vagal stimulation there is an increase in AcH leading to a prolonged conduction time of the SA node, resulting in a decreased firing rate of the node and a decrease in the contractile forces of the cardiac cells [19]. The dose response of AcH is linear until concentration reaches levels where an increase in dose no longer changes the response of the SA node and levels no longer diminish during inspiration thereby blunting HF output and decreasing HRV even as parasympathetic tone continues to increase [10, 20]. Modulation of HF power decreases with the increased AcH lowering the HF measure even in the presence of increased parasympathetic activity [21-23]. This leads to time domain measures being more reliable than HF measures in evaluating the parasympathetic contributions to HRV in athletes with bradycardia [8]. When HF in FFT is compared with RMSSD, the time domain measure equivalent for parasympathetic modulation, the HF overestimates parasympathetic activity expressed as greater HF power, thereby reducing the LF/HF ratio, underestimating sympathetic modulation [8, 14]. There is no research using HRV measures with athletes to determine which of the frequency domain measures best correlates to the preferred measure, RMSSD [8].

With athletes, HRV is used to evaluate training and recovery and is one of the physiological indicators of overtraining syndrome (OTS) [24-26]. Typically OTS is characterized by an increase in sympathetic activity, however endurance athletes with overtraining syndrome (OTS) presented with a lower LF/HF and a stronger correlation between RR interval length and HF power, reflecting diminished sympathetic activity [27, 28]. These parasympathetic changes are associated with a parasympathetic form of OTS, which differs from the normal parasympathetic changes that occur with endurance training, as the OTS changes are associated with fatigue and diminished performance and more closely resemble the exhaustion phase of the fight or flight reaction [29]. It is therefore important to consider an HRV measure that will accurately display the parasympathetic modulation in athletes with bradycardia in order to distinguish between parasympathetic changes that occur along with normal training and parasympathetic changes that may occur from OTS [29, 30]. Previous research deems the normalized power spectra of the AR method more sensitive than FFT to the effects of dynamic exercise, specifically to the reduction in vagal modulation and shift toward sympathetic dominance [17]. The increased sensitivity may be because AR analysis corresponds more distinctly to the specific oscillating bands of each HRV component and is better able to filter the vagal tone than the FFT analysis thereby making AR analysis a more appropriate measure than FFT analysis in those athletes with bradycardia or SA node saturation [8, 15, 17]. The advantages of AR analysis are especially important to consider for evaluating HRV in the endurance athlete who is at risk for a parasympathetic form of OTS [28, 29].

Therefore the purpose of this study is twofold. The first purpose is to compare the results between the frequency domain methods of FFT and AR for resting HRV in Division I Collegiate athletes. It is hypothesized that the correlation between frequency domain measures will be strong, but the measures will be significantly different. The second purpose is to compare the frequency domain measures with the time domain RMSSD measure. It is hypothesized that the AR analysis will have a stronger correlation and smaller discrepancy with the RMMSD values compared to the FFT analysis.

METHODS

Research Design

This study employed a cross-sectional design to examine resting time domain and frequency domain HRV variables in NCAA Division I athletes. All participants underwent a resting ECG data collection session. Data were filtered to remove ectopic beats and run through Kubios Heart Rate Variability software for analysis. The natural log transformation of the time domain measure of RMSSD and the frequency domain measures of LF power, HF power, and LF/HF and the normalized units of LF and HF were used as the HRV outcome measures.

Data collection

Participants

Sixty-seven participants (n=63 female, n=4 male, mean resting HR =54±9.22), ranging in age from 18 to 25 years old (mean =19±1.36) training with NCAA Division I athletic teams were recruited. Prior to inclusion in the study, participants filled out Health History Questionnaires and informed consent form approved by the University of Hawaii Human Study Program. Participants that self-identify in the health history questionnaires as having an allergy to adhesives or suspected pregnancy were not eligible for inclusion in this study.

Instruments

The ECG data were collected using CARDIO-CARD™ ver. 6.01ia software (Nasiff Associates, Inc., Brewerton, NY, USA). Anthropometric data collected included height (cm) measured by wall-mounted stadiometer, body mass (kg) measured by Detecto Certifier scale (Detecto, Webb City, MO, USA), and age. The ECG data were exported to Kubios Heart Rate Variability ver. 2.1 software (Biosignal Analysis and Medical Imaging Group, Dept. of Physics, University of Kuopio, Finland) to obtain time and frequency domain measures. Prior to electrode application, the skin was cleaned and prepped. The right and left arm electrodes were placed below the right and left clavicles, respectively. The right and left leg electrodes were attached to the right and left sides of the trunk, below the tenth rib on the anterior axillary line. The V5 chest electrode was placed on the left side of the fifth intercostal space on the anterior axillary line.

Experimental Procedures

The testing session was conducted in the Human Performance Laboratory at the University of Hawaii at Manoa. Participants were asked to refrain from any vigorous activities, such as playing sports and riding a bicycle as well as ingesting any caffeine, three hours prior to the data collection. Following the verbal explanation of the study procedure, all participants were asked to sign an informed consent form and fill out the Health History Questionnaire to identify exclusionary criteria.

A Board of Certification Certified Athletic Trainer collected all data. Anthropometric data were collected and recorded prior to the testing session. Following anthropometric measurements, the participant was instructed to lie down supine or semi-reclined in a comfortable position in which they could remain throughout the data collection. The investigator cleaned the electrode placement sites and the electrodes were applied to designated positions. After 10 minutes of resting in comfortable position, the ECG was recorded for 15 minutes. The participant was instructed to relax and breathe at their normal, self-determined pace, remain as steady as possible, and not to fall asleep during the data collection period.

Following the data collection procedure, the ECG output was used to calculate heart rate variability. CARDIO-CARD™ data were filtered and ectopic beats were removed prior to analysis. Electrocardiographic data were exported into Kubios Heart Rate Variability Software Version 2.0 (University of Kuopio, Kuopio, Finland) to assess time and frequency domain measures. Data were smoothed using the low-level artifact correction. Trend components were removed using a Smooth n Priors to remove the influence of the VLF and filter any artifact. Frequency bands for HRV analysis were set as follows: VLF (0-0.04 Hz), LF (0.04-0.15 Hz), and HF (0.15-0.4 Hz). Interpolation of the interbeat intervals (RR series) was set at 4 Hz. Window width for FFT was set at 256 seconds with the window overlap set at 50%. The AR spectrum used model order 16 with no factorization. The most stable five minute data period was selected for analysis. [1]

Statistical Analysis

The SPSS version 24 with a significance level set at $p<0.05$ was used for all statistical analyses (IBM Inc., Chicago, IL). The RMSSD, LF FFT power, LF AR power, HF FFT power, HF AR power, LF/HF FFT and LF/HF AR data were transformed using natural log transformation in order to obtain normal distribution. The LF FFT nu, LF AR nu, HF FFT nu and HF AR nu were normally distributed and were therefore used without transformation. A paired-samples *t*-test was used to compare the Log LF FFT power and Log LF AR power, LF

FFT nu and LF AR nu, the Log HF FFT power and Log HF AR power, HF FFT nu and HF AR nu, and LF/HF FFT and LF/HF AR. Pearson product correlation was used to compare Log LF power, LF nu, Log HF power, HF nu and Log LF/HF between the FFT and AR analyses. Intraclass Correlation Coefficient (ICC) and standard error of the measurement (SEM) were reported using the methods outlined by Shrout and Fleiss for ICC (1,1) [31]. A Bland-Altman plot was calculated with limits of agreement reported and linear regression analysis was used as a diagnostic procedure to determine if there was any proportional bias between the residuals [32]. Pearson product correlation was used to compare the time domain measure of Log RMSSD with the frequency domain measures of Log LF, LF nu, Log HF, HF nu and Log LF/HF ratio for both FFT and AR.

Table 1.1: Descriptive statistics of the non-transformed Heart Rate Variability (HRV) data As the data are not normally distributed, the minimum, median and maximum are presented along with the mean and standard deviation. The time domain measure is the root mean square of the standard deviation of the RR intervals (RMSSD). The frequency domain measures are presented as both fast Fourier transformation, indicted with FFT, and autoregressive analysis, indicated with AR. The frequency domain measures include low frequency power (LF) in m^2, LF in normalized units (nu) where the very low frequency is removed, high frequency power (HF) in m^2, HF in normalized units (nu) with the very low frequency removed, and the ratio of LF/HF.

Descriptive Statistics

	Minimum	Median	Maximum	Mean	Std. Deviation	N
RMSSD	15.7	86.2	240.1	93.0269	47.65242	67
LF FFT m2	54	994.0	12805	1684.52	2298.443	67
LF AR m2	80	996.0	12011	1856.13	2211.653	67
LF FFT nu	6.1	35.3	68.6	35.81343	16.160998	67
LF AR nu	6.0	40.0	71.6	37.80896	16.188106	67
HF FFT m2	85	2154.0	12330	2966.79	2767.891	67
HF AR m2	87	2490.0	13482	3216.63	2948.614	67
HF FFT nu	31.4	64.6	93.4	64.07612	16.121020	67
HF AR nu	28.3	59.9	93.8	62.07463	16.169719	67
LF/HF FFT	.065	.546	2.189	.67390	.486343	67
LF/HF AR	.064	.670	2.528	.74039	.541345	67

Table 1.2: Test of Normality for the log transformed HRV data
The normalized units were normally distributed and were therefore not log transformed and reanalyzed using Shapiro-Wilk Statistic. The log transformed time domain measure used is the root mean square of the standard deviation of RR intervals (Log RMSSD) and frequency domain measures used include low frequency (Log LF) power, LF normalized units (nu), high frequency (Log HF) power, HF nu and LF/HF (Log LG/HF) for both the fast Fourier transformation (FFT) and autoregressive analysis (AR).

Tests of Normality

	Shapiro-Wilk		
	Statistic	df	Sig.
Log RMSSD	.977	67	.251
Log LF FFT	.989	67	.823
Log LF AR	.987	67	.697
LF FFT nu	.968	67	.085
LF AR nu	.980	67	.335
Log HF FFT	.971	67	.115
Log HF AR	.967	67	.070
HF FFT nu	.968	67	.078
HF AR nu	.979	67	.320
Log LFHF FFT	.972	67	.130
Log LFHF AR	.978	67	.265

RESULTS

Descriptive statistics for the non-transformed data are presented in Table 1.1. A paired-samples *t*-test (Table 1.4) indicated that scores were significantly higher for the AR measures of Log LF power ($t(66)=-2.76$, $p=.007$), LF nu ($t(66)=-2.39$, $p=.020$) and the Log LF/HF ($t(66)=-2.49$, $p=.015$) compared to the FFT measurements. The HF nu was the only measure that was significantly higher with FFT ($t(66)=2.39$, $p=.020$). There was no significant difference between the Log HF power ($t(66)=-1.62$, $p=.110$). Even with the significantly different scores, the Pearson product correlations between the frequency domain measures were both strong and significant ($p<.001$) (table 1.3). Intraclass correlation coefficient and standard error of the measurement are presented in table 1.5. Bland Altman plot is presented in Figure 1.1.

Table 1.3: Paired Samples Correlations
The frequency domain measures of fast Fourier technique (FFT) and autoregressive analysis (AR) are compared using the log transformation of the low frequency power (Log LF), high frequency power (Log HF) and LF/HF (Log LF/HF). The LF and HF normalized units (nu) are normally distributed therefore they were not log transformed. Correlations are strong and significant.

Paired Samples Correlations

	N	Correlation	Sig.
Log LF FFT & Log LF AR	67	.891	.000*
LF FFT nu & LF AR nu	67	.911	.000*
Log HF FFT & Log HF AR	67	.955	.000*
HF FFT nu & HF AR nu	67	.910	.000*
Log LFHF FFT & Log LFHF AR	67	.914	.000*

*. Correlation is significant at the 0.05 level (2-tailed)

Table 1.4: Paired Samples Test
Comparisons are made between the Frequency Domain Measures of fast Fourier technique (FFT) and autoregressive analysis (AR) for the log transformation of the low frequency power (Log LF), high frequency power (Log HF), and LF/HF (Log LF/HF). The LF and HF normalized units (nu) are normally distributed therefore they are not log transformed. Only the HF was not significantly different between FFT and AR analyses. Only the HF nu was higher with FFT compared to AR.

Paired Samples Test

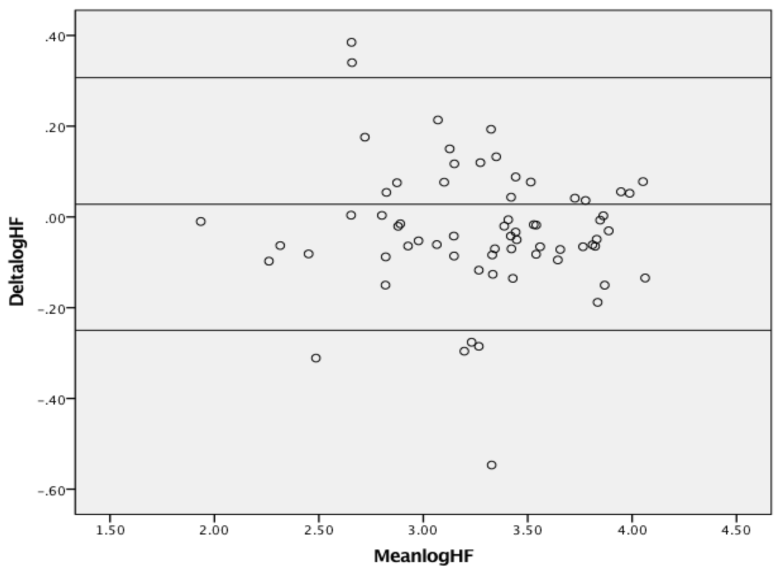
	Paired Differences							
				95% Confidence Interval of the Difference				
	Mean	Std. Deviation	Std. Error Mean	Lower	Upper	t	df	Sig. (2-tailed)
Log LF FFT - Log LF AR	-.07220	.21407	.02615	-.12441	-.01998	-2.761	66	.007*
LF FFT nu – LF AR nu	-1.9955	6.8283	.8342	-3.6611	-.3300	-2.392	66	.020*
Log HF FFT – Log HF AR	-.02819	.14238	.01739	-.06292	.00653	-1.621	66	.110
HF FFT nu – HF AR nu	2.0015	6.8457	.8363	.3317	3.6713	2.393	66	.020*
Log LFHF FFT – Log LFHF AR	-.04399	.14435	.01764	-.07920	-.00878	-2.494	66	.015*

* significant at the 0.05 level (2-tailed).

Table 1.5: ICC and SEM
Intraclass correlations (ICC) and standard error of the measurement (SEM) are presented for the Frequency Domain Measures of fast Fourier technique (FFT) and autoregressive analysis (AR) for the log transformation of the low frequency power (Log LF), high frequency power (Log HF), and LF/HF (Log LF/HF). The LF and HF normalized units (nu) are normally distributed therefore they are not log transformed.

	ICC	SEM
Log LF FFT- Log LF AR	.879	0.07
LF nu FFT – LF nu AR	.905	2.10
Log HF FFT-Log HF AR	.954	0.03
HF nu FFT – HF nu AR	.904	2.12
Log LF/HF FFT – Log LF/HF AR	.907	0.04

Figure 1.1: Bland Altman plot for log transformation of the high frequency power (Log HF) shows seven outliers and strong limits of agreement. Based on linear regression of the residuals there was no significant difference (p=.617).



Pearson product correlations between Log RMSSD and the frequency domain measures for both FFT and AR were also significant (Table 1.6). The Log HF power measures showed the strongest correlation to Log RMSSD with the AR Log HF power, Pearson's $r(67)=.967$, $p<.001$, slightly better than the FFT HF power Pearson's $r(67)=.935$, $p<.001$. The other measures, while significant, did not display strong correlations with RMSSD.

Table 1.6: Correlations between the time domain and frequency domain measures
Correlations between the log transformation the root mean square of the standard deviation of RR intervals (Log RMSSD) and the fast Fourier transformation (FFT) and autoregressive (AR) analysis for the log transformation of low frequency power (Log LF), high frequency power (Log HF) and the LF/HF (Log LF/HF). The LF and HF normalized units (nu) are normally distributed and therefore not log transformed. All Correlations are significant however the HF has the strongest correlation with RMSSD. The LF/HF is supposed to be a measure of sympathetic activity however it does not show a very strong negative relationship with the parasympathetic RMSSD.

Correlations

		Log LF FFT	LF FFT nu	Log HF FFT	HF FFT nu	Log LFHF FFT	Log LF AR	LF AR nu	Log HF AR	HF AR nu	Log LFHF AR
Log RMSSD	Pearson Correlation	.662**	-.306*	.935**	.302*	-.364**	.708**	-.378**	.967**	.376**	-.449**
	Sig. (2-tailed)	.000	.012	.000	.013	.002	.000	.002	.000	.002	.000
	N	67	67	67	67	67	67	67	67	67	67

*. Correlation is significant at the 0.05 level (2-tailed).
**. Correlation is significant at the 0.01 level (2-tailed).

DISCUSSION

As the interest in using HRV measures for training and recovery studies continues to increase there is an increased need for research into methodological considerations, such as FFT and AR, to determine appropriate outcomes of HRV in highly trained athletes. Typically, the HF power in FFT has an increase in the amount of "noise" as it does not provide clear peaks associated with respiration which results in higher HF power measures in FFT compared to AR however no statistically significant difference was indicated in this study [13-15, 17, 20, 33, 34]. As the parasympathetic modulation decreases with AcH saturation, the peaks may be less clear in the trained athlete for both the AR and FFT measures, which would explain why HF power was the only measure not significantly different between FFT and AR in the current study [13]. Our data showed that the removal of the thermoregulatory effects of the VLF on the HF power produced significantly lower measures of HF nu in AR, which has been demonstrated by Silva et al. in normotensive and hypertensive patients [14]. In the current study, this is the only measure where the FFT was higher than AR possibly because the FFT noise overestimated the contribution of the HF or underestimated the value of the VLF in athletes who typically have more muscle mass and a higher resting metabolism. As a result, the LF/HF measure was significantly lower in the FFT compared to that of AR, also consistent with previous research [33, 34]. As this is a ratio of the LF to HF power, if the AR and FFT measures were consistent in terms of power distribution, and LF/HF was truly able to reflect sympathovagal balance, any differences would not be statistically significant because overestimation in both LF and HF by one measure would be eliminated in the ratio calculation, especially in a methodology that does not involve paced respiration, therefore the value of the LF/HF remains questionable [12, 35]. The mean Log LF value for FFT was significantly lower compared to that of AR, as seen in the literature [33, 34]. The untransformed data range for LF power in FFT was from $54m^2$ (minimum) to $12805m^2$ (maximum) while the AR data was $80m^2$ (minimum) to $12011m^2$ (maximum). The wider range in the FFT measure could indicate a greater overlap between the LF and HF bands where bands that should have been considered in HF were calculated into the LF measures thereby inflating the maximum measure, however this only lead to a significant difference in the LF power measures, not the HF power. Therefore either the HF power was not overestimated or the overestimation in the HF power from lack of separation in the bands resulted in similar measures for the FFT and the AR. Pearson product correlation between the two measures was strong and significant, however the AR and FFT techniques produced significantly different results in an athletic population that has high HRV and low RHR. This finding is consistent with the conducted on healthy individuals with high levels of HRV and further support the recommendation of not using the frequency domain measures of AR and FFT interchangeably [13].

The time domain measure of RMSSD and the frequency domain measure of HF power are both associated with parasympathetic modulation, of which RMSSD has been recommended for highly trained athletes [8]. The RMSSD is calculated such that the higher the number the greater the amount of variance between the squares of the mean difference of the RR intervals. As the frequency domain measures explain the variance in terms of power by placing the RR intervals into corresponding frequency bands, the HF and RMSSD should yield strong correlations [1]. The HF power FFT (r^2=.935) and AR (r^2=.967) measures are both strongly correlated to RMSSD with the AR measure having a slightly higher correlation confirming AR as having an advantage in the assessment of parasympathetic measures of HRV in athletes at rest [15]. The accompanying bradycardia that is associated with training will increase vagal activity lengthening RR intervals, therefore the ability of the AR technique to smooth and separate the frequency bands would explain the larger correlation to RMSSD [27]. As the LF power is a mix of sympathetic and parasympathetic influence, it was expected that the correlations with the parasympathetic RMSSD were not strong. Interestingly the removal of the VLF to normalize the LF (LF nu) resulted in a negative correlation with RMSSD similar to that of LF/HF, which would make the LF nu as an indicator for sympathetic modulation [1, 12]. It is possible that the higher metabolism and higher muscle mass of an athlete resulted in higher VLF, which once removed decreased the LF however this cannot be confirmed as no metabolic analysis or body composition analysis were obtained. Previous research by Esco, et al. has highlighted the relationship between skinfold thickness and cardiovascular autonomic control, however those studies did not use highly trained athletes and LF nu was not an HRV outcome measure therefore no direct comparisons can be made to our study [36, 37]. While our study was the first to report a negative correlation between LF nu and RMSSD, the correlation was not strong (r^2= -.306 for FFT, r^2=-.378 for AR) and therefore the LF nu should not be interpreted as a strong measure of sympathetic activity. While a negative correlation between the LF/HF ratio and RMSSD found in the current study was expected based on the consensus of LF/HF ratio as an indicator of sympathetic modulation, the correlation was not as strong as would be expected (r^2=-.364 for FFT, r^2=-.449 for AR) [35]. Caution should be taken when using LF/HF ratio as a measure of sympathovagal balance in an athletic population. Based on the current study, the HF power in AR is the most appropriate frequency domain measure of parasympathetic modulation, as indicated by the highest correlation with RMSSD in a highly trained athletic population.

Training studies continue to use either the AR or FFT measures without further explanation as to the justification for choosing the appropriate measure. As the use of HRV to monitor training and recovery becomes more prevalent in practice as well as in the literature, it is important to have consistency in the data collection method as well as the measures used. Since the AR and FFT measures cannot be used interchangeably, it is important not only to make comparisons within frequency domain measurements that use the same technique but also for researchers to indicate the method used to obtain the results to avoid misrepresentation. The time domain measure of RMSSD remains the preferred method of examining daily HRV change and parasympathetic modulation levels in athletes as it can be used in conjunction with SA node saturation and has the least amount of variation between studies. Should an alternative frequency domain measure be required, the HF power AR measure is recommended for this population, however it should be used with caution as the peaks may not be as clearly defined and an underestimation of parasympathetic modulation may be made.

Chapter 2

Examining the Relationship between the Recovery-Stress Questionnaire and Heart Rate Variability in NCAA Division I Collegiate Athletes

INTRODUCTION

In an effective training program, the accumulation of physical stresses are intended to produce overload resulting in physical adaptations that would lead to an increase in parasympathetic activity at rest [30, 38]. However if the accumulation of stresses is too great, continued for too long or is combined with psychological stressors it can lead to overtraining [24, 25, 28]. Overtraining syndrome (OTS) is typically characterized by a decline in performance with a loosely defined set of physiological and psychological markers, lacking a defined set of diagnostic criteria [24, 26, 39]. Though OTS is typically associated with maladaptation to training it is really the accumulation of stresses without adequate recovery that leads to the inability to meet the training demands [38, 40, 41]. Evaluating recovery on a regular basis can identify the increased need for rest prior to performance declines allowing an athlete to resume normal training and competition, following a brief respite [42, 43]. Examination of the stress-recovery balance for an individual should rely on subjective measures such as rating of perceived exertion (RPE) and fatigue as well as objective measures of physiological changes especially those associated with autonomic function [24, 25, 28]. Current tools used in research and clinical settings to evaluate recovery include the Recovery-Stress Questionnaire for Athletes (RESTQ-Sport) to monitor levels of general as well as sport specific stresses and recovery, and heart rate variability (HRV), a noninvasive tool for assessing the balance of the autonomic nervous system (ANS) [4, 24, 28, 44].

The RESTQ-Sport, a validated questionnaire sensitive to training and non-training stresses and recovery, evaluates the athlete using nineteen different scales divided into general and sport-specific stress and recovery scales [38]. The questionnaire assesses potential stressors related to life, performance and the physiological aspects of stress, their subjective consequences and the frequency of the events over the past three days and nights [44]. Of the general stress scales, the scale specifically labeled general stress, correlates high with the remaining stress scales and is considered to be most reflective of the stress level of the athlete with those scoring high having larger amounts of stress [44]. This questionnaire is sensitive to the ebb and flow of a normal training cycle providing a conceptual framework best suited to identify those at risk for OTS when combined with other indicators such as physiological changes in HRV, which also undergoes changes during the training cycle based on the physical demands required to produce supracompensatory changes, however the relationship between the RESTQ-Sport and any specific physiological variable has not been identified [30, 38, 45].

Heart rate variability is evaluated using time domain measures, the rate between successive R-R intervals, and frequency domain measures, a function of how power (variance) distributes as a function of frequency [1]. The use of time domain measures such as the root mean square of the standard deviation of normal RR intervals (RMSSD) are more sensitive to the parasympathetic changes in highly trained athletes. The frequency domain measure of high frequency power (HF), associated with parasympathetic modulation, can be blunted under training induced bradycardia as acetylcholine (AcH) saturation of the sinoatrial node and heightened vagal activity occur without the associated reflection of increased HF spectral analysis. [7-9] The frequency domain measure of LF power reflects both sympathetic and parasympathetic modulation, making the low frequency to high frequency ratio (LF/HF) a measure of sympathetic activity [1]. The ANS response to both objective and subjective stresses involves the same mechanism of parasympathetic withdrawal and sympathetic activation, however the slow rate of metabolism of norepinephrine by the cardiac tissue may cause a slower withdrawal of sympathetic activity following exercise if there is an increase in epinephrine from the presence of non-exercise stressors [4, 19, 46]. Normal HRV fluctuates from day to day based on stress state where a decrease in daily parasympathetic HRV measures may reflect a lack of recovery from the previous day's training or indicate an increased stress state [47, 48]. Increases in the RMSSD or HF power measures could reflect adequate recovery, a positive adaptation to training or a readiness to compete, or occur because the athlete is experiencing a lower amount of non-training stress [21, 47]. In order to determine if these changes are related to training or non-training stresses, additional information about the previous day's training or a subjective questionnaire would improve the use of HRV as a measure of ANS activity [4, 47, 49, 50].

Physiological changes in OTS are typically those associated with an increase in sympathetic modulation including a reduction in HRV and an increase in resting HR [24, 25]. There is also the potential for a parasympathetic form of OTS in which there is an increase in parasympathetic modulation therefore one measure alone cannot be used to diagnose OTS [24, 25, 29, 39]. Endurance athletes are at the greatest risk for parasympathetic OTS presenting with a lower LF/HF ratio indicating diminished sympathetic activity along with an increase in fatigue and subjective reporting of diminished recovery [27, 29, 51]. Without the inclusion of subjective information, changes in HRV that reflect improved parasympathetic modulation alone could be mistaken for positive changes in training and a readiness to increase activity instead of the ANS response to the alarm stage of the fight or flight response [19, 29]. As HRV is sensitive to changes in the cardiac ANS regardless of mechanism subjective data can be used in conjunction with HRV to determine if these changes are related more to the objective stress or subjective stresses [24, 28, 39, 52, 53]. The ability to validate an established questionnaire that differentiates objective and subjective stressors with HRV would be useful in determining appropriate training and recovery however a questionnaire like the RESTQ-Sport that has been used with endurance athletes may not produce the same results in non-endurance athletes [38, 54, 55].

Therefore the purpose of this study was to examine the relationship between the 19 established RESTQ-Sport scales and the physiological variables, RHR, RMSSD, HF power and LF/HF for NCAA Division I Collegiate athletes. A secondary purpose was to determine if endurance trained athletes and non-endurance trained athletes have the same relationship between the RESTQ-Sport and the physiological variables.

METHODS

Research Design

This study employed a cross-sectional design to examine objective and subjective factors associated with training stresses. All participants took the RESTQ-Sport prior to undergoing a resting HRV data collection session. Resting heart rate, the time domain measure of RMSSD, the fast Fourier transformation (FFT) frequency domain measures of HF power and LF/HF and the autoregressive (AR) analysis frequency domain measures of HF power and LF/HF were used as the HRV outcome measure. Subjective stress levels assessed using the RESTQ-Sport served as the independent variable. The entire participant group was evaluated together to determine the relationship between the RESTQ-Sport scores and the physiological variables. Participants were then further divided into two groups based on their training type, endurance or non-endurance to determine if the relationship between the RESTQ-Sport scores and the physiological measures was different among athletes with different types of training.

Cross-sectional data collection

Participants

Sixty-Six participants, ranging in age from 18 to 25 (19.7±1.36) years old training with NCAA Division I athletic teams were recruited (table 2.1). Prior to inclusion in the study, participants filled out Health History Questionnaires, Training questionnaire, RESTQ-Sport [51], and informed consent form approved by the University of Hawaii Human Study Program. Participants that self-identify in the health history questionnaires as having an allergy to adhesives or suspected pregnancy were not eligible for inclusion in this study.

Table 2.1: Demographics: Demographics including age in years (yrs) and resting heart rate (RHR) in beats per minute (bpm) for the full data set as well as the endurance and non-endurance group members are listed.

		Age (yrs)	RHR (bpm)
Full data set	N=66 (4 male)	19.8±1.39	54±9.22
Endurance athletes	N=35 (0 male)	19.2±1.40	51±9.14
Non-endurance athletes	N=31 (4 male)	20.3±1.17	58±8.00

Instruments

The ECG data were collected using CARDIO-CARD™ ver. 6.01ia software (Nasiff Associates, Inc., Brewerton, NY, USA). Anthropometric data collected included height (cm) measured by wall-mounted stadiometer, body mass (kg) measured by Detecto Certifier scale (Detecto, Webb City, MO, USA), and age. The ECG data were exported to Kubios Heart Rate Variability ver. 2.1 software (Biosignal Analysis and Medical Imaging Group, Dept. of Physics, University of Kuopio, Finland) to obtain time and frequency domain measures. Prior to electrode application, the skin was cleaned and prepped. The right and left arm electrodes were placed below the right and left clavicles, respectively. The right and left leg electrodes were attached to the right and left sides of the trunk, below the tenth rib on the anterior axillary line. The V5 chest electrode was placed on the left side of the fifth intercostal space on the anterior axillary line.

The RESTQ-Sport (appendix D) is a 77 item questionnaire that assess the previous three days and nights using a six point Likert Scale. Each Likert choice is given an associated numerical value from zero to six and the score from four items are added together to obtain a score for one of the stress or recovery scales. The items associated with each scale are non-consecutive and are outlined with the scoring instructions in the accompanying scoring key. The seven life stress or general stress scales include the following scales: general stress, emotional stress, social stress, conflicts-pressures, fatigue, lack of energy and physical complaints. The five general recovery scales include: success, social recovery, physical recovery, general well-being and sleep quality. The three sport-specific stress scales include disturbed breaks, emotional exhaustion and injury. The four sport-specific recovery scales include: being in shape, personal accomplishment, self-efficacy and self-regulation. [44]

Experimental Procedures

The testing session was conducted in the Human Performance Laboratory at the University of Hawaii at Manoa. Participants were asked to refrain from any vigorous activities, such as playing sports and riding a bicycle as well as ingesting any caffeine, three hours prior to the data collection. Following the verbal explanation of the study procedure, all participants were asked to sign an informed consent form, fill out the Health History Questionnaire and the RESTQ-Sport to identify exclusionary criteria and current stress level, respectively.

A Board of Certification Certified Athletic Trainer collected all data. Anthropometric data were collected and recorded prior to the testing session. Following anthropometric measurements, the participant was instructed to lie down supine or semi-reclined in a comfortable position in which they could remain throughout the data collection. The investigator cleaned the electrode placement sites and the electrodes were applied to designated positions. After 10 minutes of resting in comfortable position, the ECG was recorded for 15 minutes. The participant was instructed to relax and breathe at their normal, self-determined pace, remain as steady as possible, and not to fall asleep during the data collection period.

Following the data collection procedure, the ECG output was used to calculate heart rate variability. The RR intervals were visually inspected to remove any ectopic beats. The filtered ECG data were exported into Kubios Heart Rate Variability Software Version 2.0 (University of Kuopio, Kuopio, Finland) to assess time and frequency domain measures. Data were smoothed using the low-level artifact correction. Trend components were removed using a Smooth n Priors to remove the influence of the VLF and filter any artifact. Frequency bands for HRV analysis were set as follows: VLF (0-0.04 Hz), LF (0.04-0.15 Hz), and HF (0.15-0.4 Hz). Interpolation of the interbeat intervals (RR series) was set at 4 Hz. Window width for fast Fourier transformation was set at 256 seconds with the window overlap set at 50%. The AR spectrum used model order 16 with no factorization. The most stable five minute data period was selected for analysis. [1]

Statistical Analysis

The SPSS version 24 with a significance level set at $p<0.05$ was used for all statistical analyses (IBM Inc., Chicago, IL). The RESTQ-Sport Likert scale was altered from "zero to six" to “one to seven” in order to assure that none of the scores were zero [44]. The physiological variables were transformed using natural log transformation to assure normality.

Linear and Quadratic regression were used to examine the effect of the stress and recovery level as determined by the 19 RESTQ-Sport scales on the natural log transformation of the physiological variables RHR, RMSSD, the FFT and AR measures of HF power and the LF/HF. Participants were then divided into group based on training type, endurance trained (n=35) and non-endurance trained (n=31) and the regression analyses were reexamined.

RESULTS

For the entire group, using linear regression with RHR as the dependent variable, the conflicts and pressures ($F(1, 64) = 11.375$, p=.001, R^2 =.151), fatigue ($F(1,64) = 9.469$, p=.003, R^2 = .129), physical complaint ($F(1,64) = 4.206$, p=.044, R^2=.062), disturbed breaks ($F(1,64)$ =4.995, p=.029, R^2=.072), injury ($F(1,64) = 7.382$, p=.008, R^2=.103), and emotional exhaustion (F, (1,64) = 11.266, p=.001, R^2=.150) scores were significant. Emotional exhaustion was also a significant predictor of RMSSD ($F(1,64) = 5.108$, p=.027, R^2=.074). For HF FFT, emotional stress ($F(1,64) = 4.770$, p= .033, R^2= .069) and social stress ($F(1,64) = 4.779$, p=.032, R^2= .069) were significant predictors. Similarly for HF AR, emotional stress ($F(1,64) = 5.641$ p= .021, R^2= .081) and social stress ($F(1,64) = 4.105$, p= .047,R^2= .060) were significant predictors. Table 2.2 outlines the significant relationships by RESTQ-Sport category and 3 outlines the significant relationships by HR variable for the full group. Additional non-significant linear regression results for each of the RESTQ-Sport scales can be seen in tables 2.14 and 2.15 at the end of this document.

Table 2.2: Full Data Set significant linear relationship by RESTQ-Sport category
Significant linear relationships for the heart rate (HR) variables include resting heart rate (RHR), the root mean square of the standard deviation of RR intervals (RMSSD), the ratio of low frequency to high frequency power (LF/HF) and the HF power. The LF/HF and HF are frequency domain variables analyzed using either the fast Fourier technique (FFT) and autoregressive analysis (AR). The Recovery-Stress Questionnaire for athletes (RESTQ) defines the scales of either stress or recovery.

RESTQ Category	HR Variable	R	R^2	Adjusted R^2	Sig F Change	B Variable
Emotional Stress	HF FFT	.263	.069	.055	.033	.046
	HF AR	.285	.081	.067	.021	.051
Social Stress	HF FFT	.264	.069	.055	.032	.041
	HF AR	.246	.060	.046	.047	.039
Conflicts-Pressures	RHR	.388	.151	.138	.001	.007
Fatigue	RHR	.359	.129	.115	.003	.006
Physical Complaint	RHR	.248	.062	.047	.044	.006
Disturbed Breaks	RHR	.269	.072	.058	.029	.007
Emotional Exhaustion	RHR	.387	.150	.136	.001	.007
	RMSSD	.272	.074	.059	.027	.016
Injury	RHR	.322	.103	.089	.008	.005

Table 2.3: Full data set significant linear relationship by HR Variable
The heart rate (HR) variables include resting heart rate (RHR), the root mean square of the standard deviation of RR intervals (RMSSD), the ratio of low frequency to high frequency power (LF/HF) and the HF power. The LF/HF and HF are frequency domain variables analyzed using either the fast Fourier technique (FFT) and autoregressive analysis (AR). The Recovery-Stress Questionnaire for athletes (RESTQ) defines the scales of either stress or recovery.

HR Variable	RESTQ Category	R	R^2	Adjusted R^2	Sig F Change	B Variable
RHR	Conflicts-Pressures	.388	.151	.138	.001	.007
	Fatigue	.359	.129	.115	.003	.006
	Physical Complaint	.248	.062	.047	.044	.006
	Disturbed Breaks	.269	.072	.058	.029	.007
	Emotional Exhaustion	.387	.150	.136	.001	.007
	Injury	.322	.103	.089	.008	.005
RMSSD	Emotional Exhaustion	.272	.074	.059	.027	.016
LF/HF FFT	NONE					
LF/HF AR	NONE					
HF FFT	Emotional Stress	.263	.069	.055	.033	.046
	Social Stress	.264	.069	.055	.032	.041
HF AR	Emotional Stress	.285	.081	.067	.021	.051
	Social Stress	.246	.060	.046	.047	.039

With quadratic regression, for the entire group sleep quality was found to be a significant predictor of LF/HF FFT (F(2,63) = 3.515, p=.036, R^2=.100). The emotional exhaustion score was found to be a significant predictor of HF FFT (F(2,63) = 5.278, p=.037, R^2=.144) and HF AR (F(2,63) = 5.842 p= .050, R^2= .103). There were no significant relationships with RHR, RMSSD or LF/HF AR. Table 2.4 outlines the significant curvilinear relationships by RESTQ-Sport scale and table 2.5 outlines the significant curvilinear relationships by HR variable.

Table 2.4: Full data set significant curvilinear relationship by RESTQ-Sport category
Full data set significant curvilinear relationships by Recovery-Stress Questionnaire for athletes (RESTQ) scale. The heart rate (HR) variables include the frequency domain measures of high frequency power (HF) for the fast Fourier technique and autoregressive (AR) analysis and the ratio of low frequency to HF (LF/HF)

RESTQ Category	HR Variable	R	R^2	Adjusted R^2	Sig F Change	B Variable
Emotional Exhaustion	HF FFT	.379	.144	.116	.037	.183 -.007
	HF AR	.396	.156	.130	.050	.181 -.007
Sleep Quality	LF/HF FFT	.317	.100	.072	.028	-.102 .003

Table 2.5: Full data set significant curvilinear Relationship by HR Variable
Significant curvilinear relationships by heart rate (HR) variables including resting heart rate (RHR), the root mean square of the standard deviation of RR intervals (RMSSD), the ratio of low frequency to high frequency power (LF/HF) and the HF power. The LF/HF and HF are frequency domain variables analyzed using either the fast Fourier technique (FFT) and autoregressive analysis (AR). The Recovery-Stress Questionnaire for athletes (RESTQ) defines the scales of either stress or recovery.

HR Variable	RESTQ Category	R	R^2	Adjusted R^2	Sig F Change	B Variable
RHR	NONE					
RMSSD	NONE					
LF/HF FFT	Sleep Quality	.317	.100	.072	.028	-.102 .003
LF/HF AR	NONE					
HF FFT	Emotional Exhaustion	.379	.144	.116	.037	.183 -.007
HF AR	Emotional Exhaustion	.396	.156	.130	.050	.181 -.007

When subjects were divided into groups based on the type of training, endurance and non-endurance, the endurance group had a greater number of significant predictors. The significant linear regression results by RESTQ-Sport scale for the endurance group is presented in table 2.6 and for the non-endurance group is presented in table 2.7. With linear regression using RHR as the dependent variable, the emotional stress, ($F(1,33) = 8.138$, p=.007, R^2=.198), conflicts-pressures ($F(1,33) = 9.311$, p=.004, R^2=.220), fatigue ($F(1,33) = 10.203$, p=.003, R^2=.236), physical complaint ($F(1,33) = 5.476$, p=.025, R^2=.142), disturbed breaks ($F(1,33)$ =8.324 , p=.007, R^2=.201) and emotional exhaustion ($F(1,33) = 17.147$, p<.001, R^2=.342) scores were significant for the endurance group while for the non-endurance group only success ($F(1,29) = 10.440$, p=.003, R^2=.265) was significant for RHR. With RMSSD as the dependent variable for the endurance group general stress ($F(1,33) = 6.670$, p=.014, R^2=.168), lack of energy ($F(1,33) = 7.468$, p=.010, R^2=.185), and emotional exhaustion ($F(1,33) = 8.178$, p=.007, R^2=.199) were significant predictors while the non-endurance group had no significant predictors of RMSSD. With LF/HF FFT as the dependent variable for the endurance group general stress ($F(1,33) = 5.602$, p=.024, R^2=.145), social recovery ($F(1,33) = 18.723$, p<.001, R^2=.362), and general well-being ($F(1,33) = 9.555$, p=.004, R^2=.225) were significant predictors while injury ($F(1,29) = 4.513$, p=.043, R^2=.135), and self-regulation ($F(1,29) = 7.811$, p=.009, R^2=.212) were significant predictors of LF/HF FFT for the non-endurance group. For LF/HF AR in the endurance group general stress ($F(1,33) = 5.919$, p=.021, R^2=.152), social recovery ($F(1,33)$ = 16.563, p<.001, R^2=.334), and general well-being ($F(1,33) = 7.839$, p=.008, R^2=.192) were also significant however only self-regulation ($F(1,29) = 8.489$, p=.007, R^2=.226) was significant for LF/HF AR with the non-endurance group. With HF FFT in the endurance group general stress ($F(1,33) = 4.201$, p=.048, R^2=.113), lack of energy ($F(1,33) = 4.343$, p=.045, $R^2 = .116$) and emotional exhaustion (F(1,33) = 6.646, p=.015, R^2=.168) were significant predictors and with HF AR general stress (F(1,33) = 7.057, p=.012, R^2=.176), lack of energy (F(1,33) = 10.392, p=.003, R^2=.239) and emotional exhaustion (F(1,33) = 10.501, p=.003, R^2=.241) were significant predictors. In the non-endurance group, there were no significant predictors of HF FFT or HF AR. The significant linear regression results by HR variable can be seen in table 2.8 for the endurance group and in table 2.9 for the non-endurance group.

Table 2.6: Endurance athlete significant linear relationship by RESTQ-Sport category
The heart rate (HR) variables include resting heart rate (RHR), the root mean square of the standard deviation of RR intervals (RMSSD), the ratio of low frequency to high frequency power (LF/HF) and the HF power. The LF/HF and HF are frequency domain variables analyzed using either the fast Fourier technique (FFT) and autoregressive analysis (AR). The Recovery-Stress Questionnaire for athletes (RESTQ) defines the scales of either stress or recovery.

RESTQ Category	HR Variable	R	R^2	Adjusted R^2	Sig F Change	B Variable
General Stress	RMSSD	.410	.168	.143	.014	.032
	LF/HF FFT	.381	.145	.119	.024	-.038
	LF/HF AR	.390	.152	.126	.021	-.041
	HF FFT	.336	.113	.086	.048	.052
	HF AR	.420	.176	.151	.012	.067
Emotional Stress	RHR	.445	.198	.174	.007	.013
Conflicts-Pressures	RHR	.469	.220	.196	.004	.008
Fatigue	RHR	.486	.236	.213	.003	.008
Lack of Energy	RMSSD	.430	.185	.160	.010	.036
	HF FFT	.341	.116	.090	.045	.056
	HF AR	.489	.239	.216	.003	.084
Physical Complaint	RHR	.377	.142	.116	.025	.008
Social Recovery	LF/HF FFT	.602	.362	.343	.000	.042
	LF/HF AR	.578	.334	.314	.000	.042
General Well-Being	LF/HF FFT	.474	.225	.201	.004	.041
	LF/HF AR	.438	.192	.167	.008	.039
Disturbed Breaks	RHR	.449	.201	.177	.007	.013
Emotional Exhaustion	RHR	.585	.342	.322	.000	.013
	RMSSD	.446	.199	.174	.007	.031
	HF FFT	.409	.168	.142	.015	.055
	HF AR	.491	.241	.218	.003	.069

Table 2.7: Non-endurance athlete significant linear relationship by RESTQ-Sport Category

The heart rate (HR) variables include resting heart rate (RHR), the root mean square of the standard deviation of RR intervals (RMSSD), the ratio of low frequency to high frequency power (LF/HF) and the HF power. The LF/HF and HF are frequency domain variables analyzed using either the fast Fourier technique (FFT) and autoregressive analysis (AR). The Recovery-Stress Questionnaire for athletes (RESTQ) defines the scales of either stress or recovery.

RESTQ Category	HR Variable	R	R^2	Adjusted R^2	Sig F Change	B Variable
Success	RHR	.514	.265	.239	.003	.009
Injury	LF/HF FFT	.367	.135	.105	.043	-.031
Self-Regulation	LF/HF FFT	.461	.212	.185	.009	-.042
	LF/HF AR	.476	.226	.200	.007	-.040

Table 2.8: Endurance athlete significant linear relationship by HR Variable

The heart rate (HR) variables include resting heart rate (RHR), the root mean square of the standard deviation of RR intervals (RMSSD), the ratio of low frequency to high frequency power (LF/HF) and the HF power. The LF/HF and HF are frequency domain variables analyzed using either the fast Fourier technique (FFT) and autoregressive analysis (AR). The Recovery-Stress Questionnaire for athletes (RESTQ) defines the scales of either stress or recovery.

HR Variable	RESTQ Category	R	R^2	Adjusted R^2	Sig F Change	B Variable
RHR	Emotional Stress	.445	.198	.174	.007	.013
	Conflicts-Pressures	.469	.220	.196	.004	.008
	Fatigue	.486	.236	.213	.003	.008
	Physical Complaint	.377	.142	.116	.025	.008
	Disturbed Breaks	.449	.201	.177	.007	.013
	Emotional Exhaustion	.585	.342	.322	.000	.013
RMSSD	General Stress	.410	.168	.143	.014	.032
	Lack of Energy	.430	.185	.160	.010	.036
	Emotional Exhaustion	.446	.199	.174	.007	.031
LF/HF FFT	General Stress	.381	.145	.119	.024	-.038
	Social Recovery	.602	.362	.343	.000	.042
	General Well-Being	.474	.225	.201	.004	.041
LF/HF AR	General Stress	.390	.152	.126	.021	-.041
	Social Recovery	.578	.334	.314	.000	.042
	General Well-Being	.438	.192	.167	.008	.039
HF FFT	General Stress	.336	.113	.086	.048	.052
	Lack of Energy	.341	.116	.090	.045	.056
	Emotional Exhaustion	.409	.168	.142	.015	.055
HF AR	General Stress	.420	.176	.151	.012	.067
	Lack of Energy	.489	.239	.216	.003	.084
	Emotional Exhaustion	.491	.241	.218	.003	.069

Table 2.9: Non-endurance athlete significant linear relationship by HR Variable
The heart rate (HR) variables include resting heart rate (RHR), the root mean square of the standard deviation of RR intervals (RMSSD), the ratio of low frequency to high frequency power (LF/HF) and the HF power. The LF/HF and HF are frequency domain variables analyzed using either the fast Fourier technique (FFT) and autoregressive analysis (AR). The Recovery-Stress Questionnaire for athletes (RESTQ) defines the scales of either stress or recovery.

HR Variable	RESTQ Category	R	R^2	Adjusted R^2	Sig F Change	B Variable
RHR	Success	.514	.265	.239	.003	.009
RMSSD	None					
LF/HF FFT	Injury	.367	.135	.105	.043	-.031
	Self-Regulation	.461	.212	.185	.009	-.042
LF/HF AR	Self- Regulation	.476	.226	.200	.007	-.040
HF FFT	None					
HF AR	None					

Using quadratic regression, the endurance group had significant relationships with all of the dependent variables while the non-endurance group only had significant relationships with RMSSD, HF FFT and HF AR. With RHR as the dependent variable self-regulation ($F(2,32) = 6.238$, p=.006, R^2=.281) was significant predictors in the endurance group. With RMSSD as the dependent variable the endurance group had significant curvilinear relationships with emotional stress ($F(2,32) = 6.929$, p=.006, R^2=.302), conflicts-pressures ($F(2,32) = 7.072$, p=.005, R^2=.307), physical complaint ($F(2,32) = 4.097$, p=.014, R^2=.204), success ($F(2,32) = 3.080$, p=.019, R^2=.161), and self-efficacy ($F(2,30) = 5.847$, p=.007, R^2=.268), while the non-endurance group had significant relationships with fatigue ($F(2,28) = 3.420$, p=.018, R^2=.196) and sleep quality ($F(2,28) = 4.053$, p= .022, R^2= .225). The LF/HF FFT ($F(2,32) = 3.331$, p=.020, R^2= .172) and LF/HF AR ($F(2,32) = 3.804$, p=.010, R^2=.192) had a significant relationship with physical complaint in the endurance group. With HF FFT, the endurance group had a significant curvilinear relationship with emotional stress ($F(2,32) = 5.535$, p=.029, R^2=.257), conflicts-pressures ($F(2,32) = 4.895$, p=.033, R^2=.234), physical complaint ($F(2,32) = 3.685$, p=.029,

R^2=.187), success (F(2,32) = 4.459, *p*=.006, R^2=.218), and self-efficacy (F(2,30) = 4.608, *p*=.008, R^2=.225) while the non-endurance group had a significant relationship only with fatigue (F(2,28) = 3.035, *p*=.024, R^2=.178). With HF AR the endurance group had a significant curvilinear relationship with emotional stress (F(2,32) = 7.551, *p*=.009, R^2=.321), conflicts-pressures (F(2,32) = 7.857, *p*=.008, R^2=.329), physical complaint (F(2,32) = 3.113, *p*=.041, R^2=.163), success (F(2,32) = 3.752, *p*=.013, R^2=.190), and self-efficacy (F(2,30) = 5.132, *p*=.008, R^2=.243), while the non-endurance group had a significant relationship only with fatigue (F(2,28) = 2.644, *p*=.033, R^2=.159). Tables 2.10 and 2.11 outline the significant curvilinear relationships for the endurance group by RESTQ-Sport scale and HR variable respectively. Tables 2.12 and 2.13 outline the significant curvilinear relationships for the non-endurance group by RESTQ-Sport scale and HR variable respectively.

Table 2.10: Endurance athlete significant curvilinear relationship by RESTQ-Sport category

The HR variables include resting heart rate (RHR), the root mean square of the standard deviation of RR intervals (RMSSD), the ratio of low frequency to high frequency power (LF/HF) and the HF power. The LF/HF and HF are frequency domain variables analyzed using either the fast Fourier technique (FFT) and autoregressive analysis (AR). The Recovery-Stress Questionnaire for athletes (RESTQ) defines the scales of either stress or recovery.

RESTQ Category	HR Variable	R	R^2	Adjusted R^2	Sig F Change	B Variable
Emotional Stress	RMSSD	.550	.302	.259	.006	.252 -.011
	HF FFT	.507	.257	.211	.029	.414 -.017
	HF AR	.566	.321	.278	.009	.493 -.020
Conflicts-Pressures	RMSSD	.554	.307	.263	.005	.146 -.004
	HF FFT	.484	.234	.186	.033	.232 -.007
	HF AR	.574	.329	.287	.008	.286 -.008
Physical Complaint	RMSSD	.451	.204	.154	.014	.163 -.007
	LF/HF FFT	.415	.172	.121	.020	-.195 .008
	LF/HF AR	.438	.192	.142	.010	-.216 .009
	HF FFT	.433	.187	.136	.029	.290 -.012
	HF AR	.404	.163	.111	.041	.283 -.011
Success	RMSSD	.402	.161	.109	.019	.195 -.006
	HF FFT	.467	.218	.169	.006	.442 -.013
	HF AR	.436	.190	.139	.013	.421 -.012
Self-Efficacy	RMSSD	.517	.268	.222	.007	.178 -.005
	HF FFT	.473	.225	.175	.008	.357 -.010
	HF AR	.493	.243	.196	.008	.361 -.011
Self-Regulation	RHR	.530	.281	.236	.006	.075 -.002

Table 2.11: Endurance athlete significant curvilinear relationship by HR Variable
The heart rate (HR) variables include resting heart rate (RHR), the root mean square of the standard deviation of RR intervals (RMSSD), the ratio of low frequency to high frequency power (LF/HF) and the HF power. The LF/HF and HF are frequency domain variables analyzed using either the fast Fourier technique (FFT) and autoregressive analysis (AR). The Recovery-Stress Questionnaire for athletes (RESTQ) defines the scales of either stress or recovery.

HR Variable	RESTQ Category	R	R^2	Adjusted R^2	Sig F Change	B Variable
RHR	Self-Regulation	.530	.281	.236	.006	.075 -.002
RMSSD	Emotional Stress	.550	.302	.259	.006	.252 -.011
	Conflicts-Pressures	.554	.307	.263	.005	.146 -.004
	Physical Complaint	.451	.204	.154	.014	.163 -.007
	Success	.402	.161	.109	.019	.195 -.006
	Self-efficacy	.517	.268	.222	.007	.178 -.005
LF/HF FFT	Physical Complaint	.415	.172	.121	.020	-.195 .008
LF/HF AR	Physical Complaint	.438	.192	.142	.010	-.216 .009
HF FFT	Emotional Stress	.507	.257	.211	.029	.414 -.017
	Conflicts-Pressures	.484	.234	.186	.033	.232 -.007
	Physical Complaint	.433	.187	.136	.029	.290 -.012
	Success	.467	.218	.169	.006	.442 -.013
	Self-efficacy	.473	.225	.175	.008	.357 -.010
HF AR	Emotional Stress	.566	.321	.278	.009	.493 -.020
	Conflicts-Pressures	.574	.329	.287	.008	.286 -.008
	Physical Complaint	.404	.163	.111	.041	.283 -.011
	Success	.436	.190	.139	.013	.421 -.012
	Self-efficacy	.493	.243	.196	.008	.361 -.011

Table 2.12: Non-endurance significant curvilinear relationship by RESTQ-Sport Category
The heart rate (HR) variables include resting heart rate (RHR), the root mean square of the standard deviation of RR intervals (RMSSD), the ratio of low frequency to high frequency power (LF/HF) and the HF power. The LF/HF and HF are frequency domain variables analyzed using either the fast Fourier technique (FFT) and autoregressive analysis (AR). The Recovery-Stress Questionnaire for athletes (RESTQ) defines the scales of either stress or recovery.

RESTQ Category	HR Variable	R	R^2	Adjusted R^2	Sig F Change	B Variable
Fatigue	RMSSD	.443	.196	.139	.018	-.104 .004
	HF FFT	.433	.178	.119	.024	-.186 .007
	HF AR	.399	.159	.099	.033	-.182 .007
Sleep Quality	RMSSD	.474	.225	.169	.022	-.177 .005

Table 2.13: Non-endurance significant curvilinear relationship by HR Variable
The heart rate (HR) variables include resting heart rate (RHR), the root mean square of the standard deviation of RR intervals (RMSSD), the ratio of low frequency to high frequency power (LF/HF) and the HF power. The LF/HF and HF are frequency domain variables analyzed using either the fast Fourier technique (FFT) and autoregressive analysis (AR). The Recovery-Stress Questionnaire for athletes (RESTQ) defines the scales of either stress or recovery.

HR Variable	RESTQ Category	R	R^2	Adjusted R^2	Sig F Change	B Variable
RHR	None					
RMSSD	Fatigue	.443	.196	.139	.018	-.104 .004
	Sleep Quality	.474	.225	.169	.022	-.177 .005
LF/HF FFT	None					
LF/HF AR	None					
HF FFT	Fatigue	.433	.178	.119	.024	-.186 .007
HF AR	Fatigue	.399	.159	.099	.033	-.182 .007

DISCUSSION

The RESTQ-Sport has previously been used to assess stress and recovery with sports such as swimming, rowing, soccer and rugby while in preparation for The Olympic Games and World Championships, it has not been widely used in with collegiate student athletes who have additional stressors such as academics [38, 44, 51]. The general stress scale under the general stress component was reported to be the most reflective of the overall stress level of the athlete; however it did not show a significant relationship to any of the physiological variables for the entire group of NCAA Division I Collegiate athletes [44]. Among the general stress component, the scales of conflicts-pressures, fatigue and physical complaint had a positive linear relationship with RHR where a higher score in the scale was associated with a higher RHR. Figures 2.1-2.3 show the positive linear relationship with the RHR on the y-axis and the adjusted RESTQ-Sport score on the x-axis. While fatigue (12.9%) could potentially be a result of lack of recovery from training, it could have been influenced by non-training stresses such as academics or travel. Increases in fatigue and conflicts/pressures (15.1%) may result in an increase in non-training stress which would increase epinephrine secretions, thereby raising RHR [19]. The injury scale (10.3%), under the sport-specific stress component, also had a weak correlation with RHR for the entire group as seen in figure 2.4. As fatigue has been shown to lead to chronic injury, these scales might be associated as shown in similar correlation to RHR and should be considered together [56]. In addition the RHR of the entire group had a significant positive linear relationship with the scales of emotional exhaustion (15%) and disturbed breaks (7.2%) under the sport-specific stress component (figures 2.5 and 2.6). The increased training load during the course of a season would be reflected in the higher scores for the sport-specific stress component. The positive linear relationship of these scores with RHR indicates that both non-training and sport-specific stresses may contribute to increase in RHR. None of the scales under the sports recovery component were correlated with RHR therefore decreases in RHR may not be interpreted as increased recovery. Regardless, the correlations found in non-training and sport-specific stresses with RHR were weak and must be used in association with other factors such as training RPE and training load for a more complete picture [38, 45, 49].

Figure 2.1: Linear regression for the Recovery-Stress Questionnaire (RESTQ) category conflicts-pressures on the x-axis and the resting heart rate (RHR) on the y-axis for the full data set.

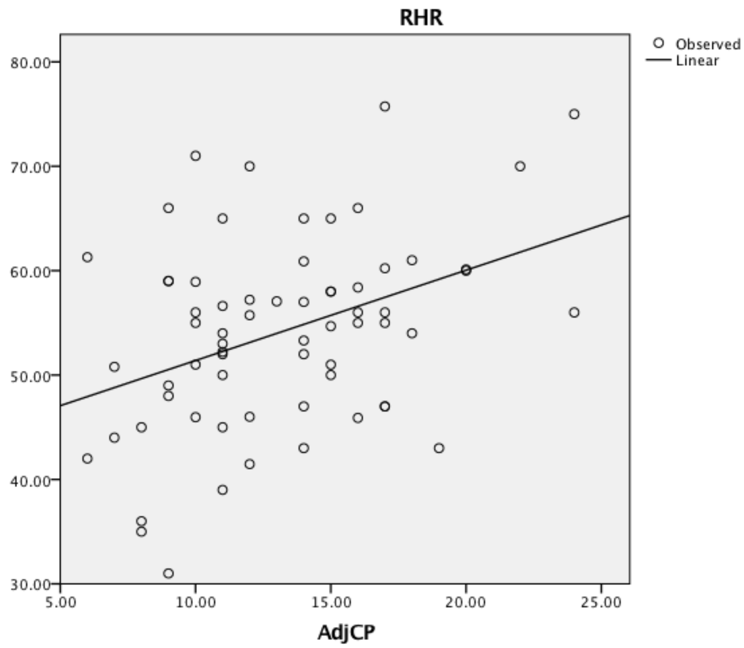


Figure 2.2: Linear regression for the Recovery-Stress Questionnaire (RESTQ) category fatigue on the x-axis and the resting heart rate (RHR) on the y-axis for the full data set.

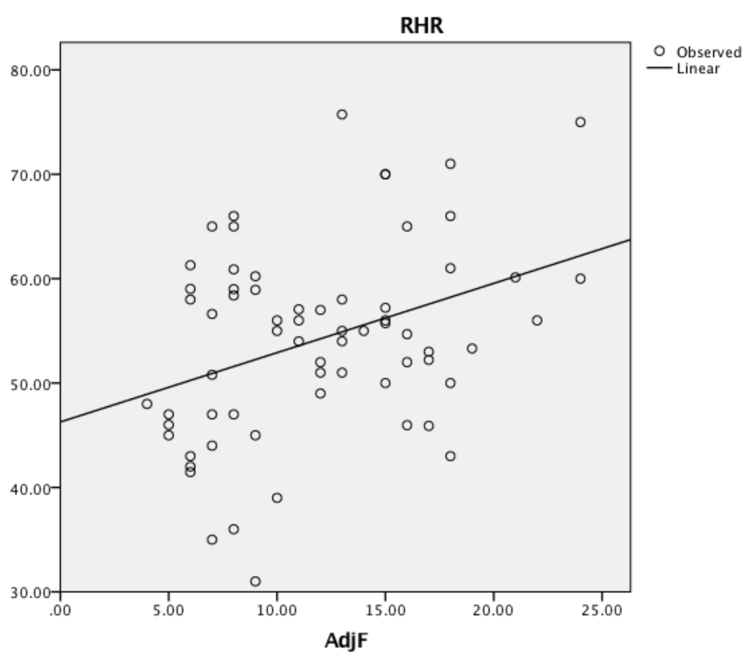


Figure 2.3: Linear regression for the Recovery-Stress Questionnaire (RESTQ) category physical complaints on the x-axis and the resting heart rate (RHR) on the y-axis for the full data set.

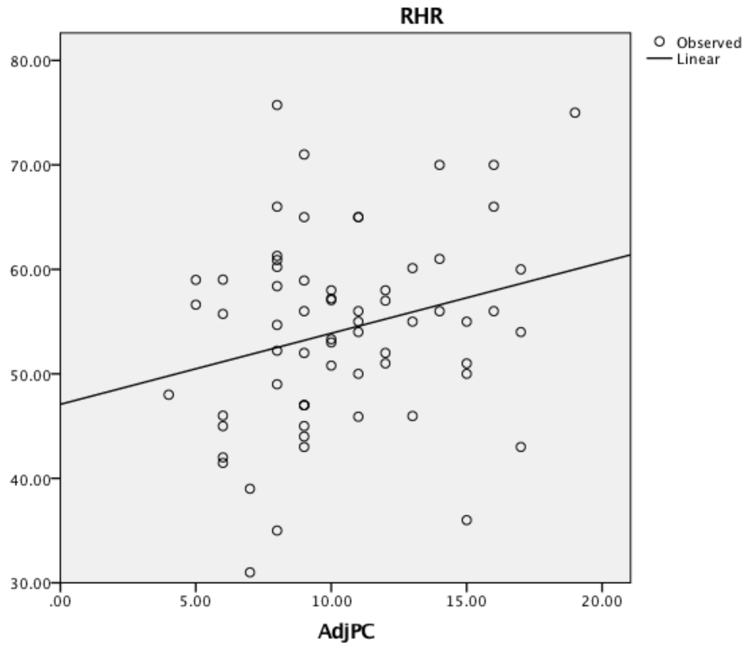


Figure 2.4: Linear regression for the Recovery-Stress Questionnaire (RESTQ) category injury on the x-axis and the resting heart rate (RHR) on the y-axis for the full data set.

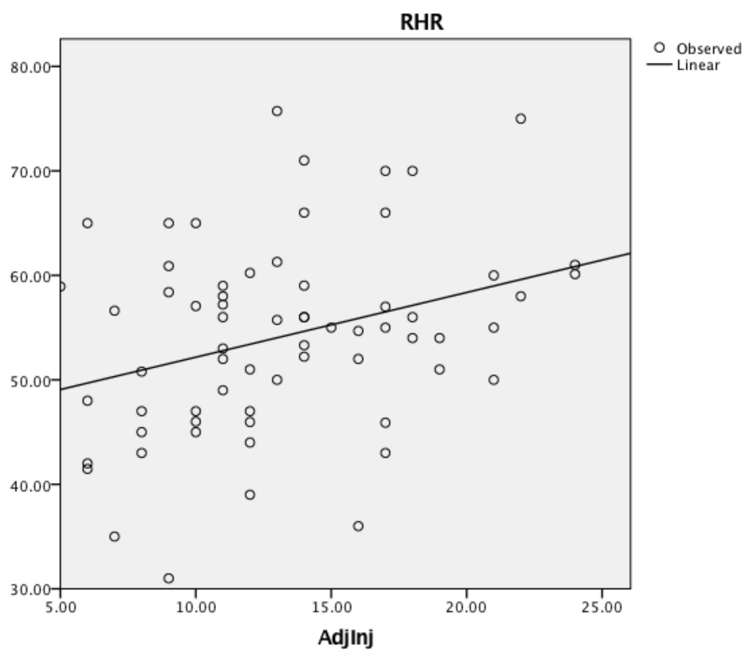


Figure 2.5: Linear regression for the Recovery-Stress Questionnaire (RESTQ) category emotional exhaustion and the resting heart rate (RHR) for the full data set.

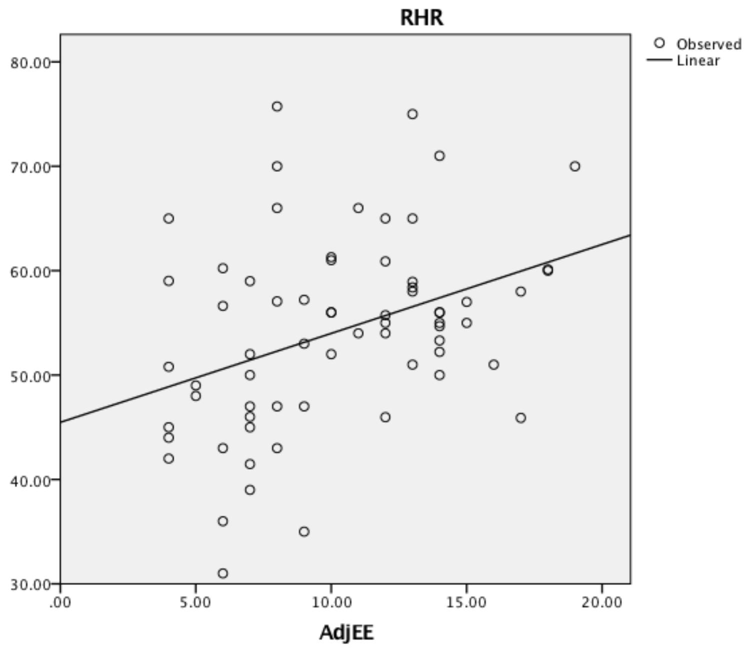
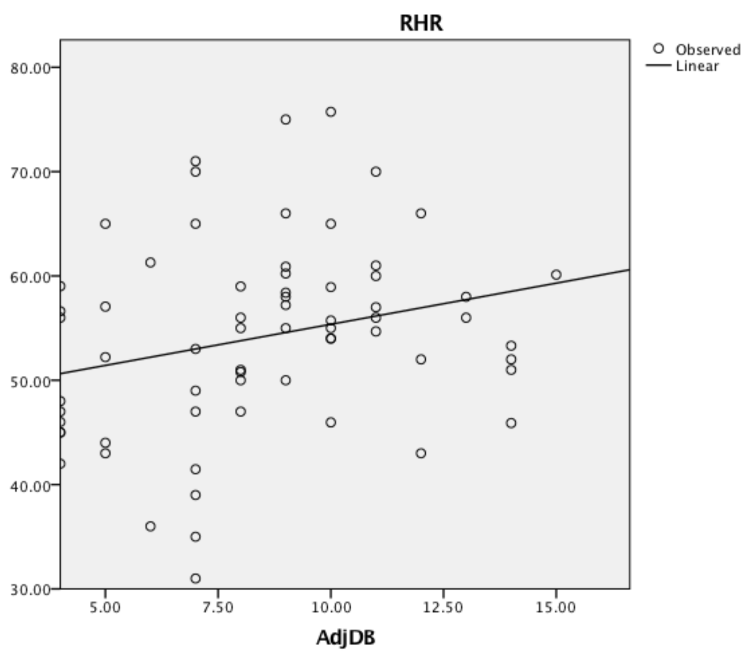


Figure 2.6: Linear regression for the Recovery-Stress Questionnaire (RESTQ) category disturbed breaks on the x-axis and the resting heart rate (RHR) on the y-axis for the full data set.



Our results indicated that the LF/HF measure, a measure of sympathetic activity, and RMSSD, the recommended predictor of parasympathetic modulation in athletes, were poor predictors of stress level in the entire group. Previous literature has recommended validating the

RESTQ-Sport against physiological variables such as HRV in order to better diagnose OTS however more research is needed to determine if the RESTQ-Sport can be applicable to student athletes or if there are different physiological variables that would be more appropriate depending on sport and training [24].

The current evidence suggests that the type of training/sport (i.e. endurance vs. non-endurance) does not influence resting HRV in the elite athletes; however it was also suggested that the subjective information such as the RESTQ-Sport might reveal different responses between these groups to training stress and the amount of recovery [18, 57, 58]. When analyses were conducted separately for the endurance group in our study, the general stress score became a weak but significant predictor for all of the HRV measures. The parasympathetic measures of RMSSD (16.8%) and HF AR (17.6%) had strong positive linear relationships with the general stress score while the LF/HF AR (15.2%) and LF/HF FFT (14.5%) had strong inverse linear relationships with the general stress score. A lower general stress score would indicate lower sympathetic activity, which should correspond with the lower LF/HF and higher RMSSD and/or HF power indicating higher parasympathetic modulation, however the relationships found in this study are opposite [44]. Figures 2.7 to 2.11 show the linear relationships for each of these variables with the adjusted general stress scale score on the x-axis and the HR variable on the y-axis. The nature of the endurance training could have resulted in the endurance athletes experiencing a parasympathetic form of OTS where the increases in HF and RMSSD measures would be related to an increase in stress levels however OTS was not diagnosed for any of these athletes therefore this assumption cannot be confirmed [29]. Based on no relationships found with the entire group, and opposite relationships found in the endurance group, it is possible that the general stress score is not reflective of the stress-state of student athletes thus not related to any of the HRV measure. The non-endurance group had no significant linear relationships with any of the stress scales however there was a significant negative linear relationships with the sport-specific recovery scales of self-regulation for LF/HF FFT (21.2%) and LF/HF AR (22.6%). Higher recovery scores and lower LF/HF measures both indicate parasympathetic modulation thus a readiness to perform; however with only one of four sport-specific recovery scales showing a relationship it is also possible that the status of sport-specific recovery has minimal influence on HRV [59, 60]. With no significant relationships for any of the parasympathetic HRV measures for the entire group or the non-endurance group, the relevance of using the general stress scale as a measure of global stress as well as the ability of HRV to determine recovery for NCAA Division I Collegiate athletes were not confirmed in the current study.

Figure 2.7: Linear regression for the Recovery-Stress Questionnaire (RESTQ) category general stress on the x-axis and the HRV time domain variable root mean square of the standard deviation of RR intervals (RMSSD) on the y-axis for the endurance group.

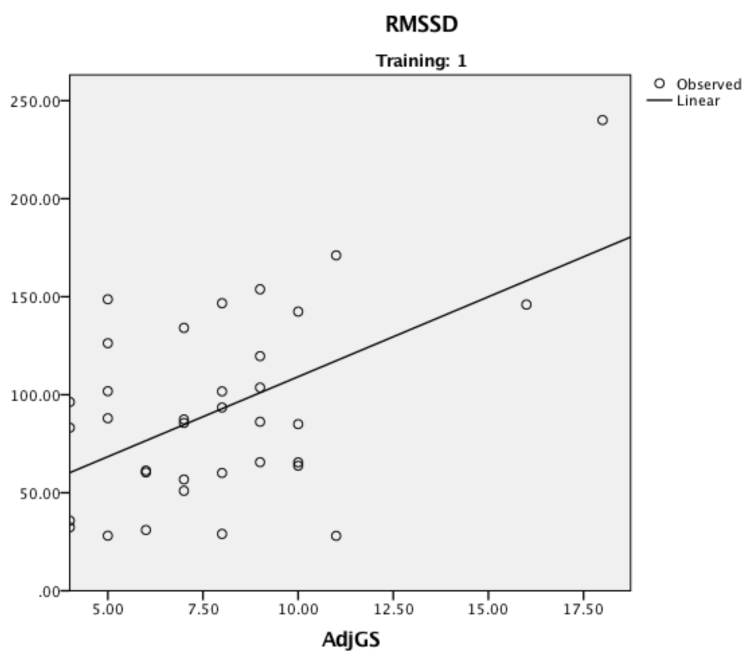


Figure 2.8: Linear regression for the Recovery-Stress Questionnaire (RESTQ) category general stress on the x-axis and the fast Fourier technique of the HRV frequency domain measure of the ratio of the low frequency to high frequency power (LF/HF FFT) on the y-axis for the endurance group.

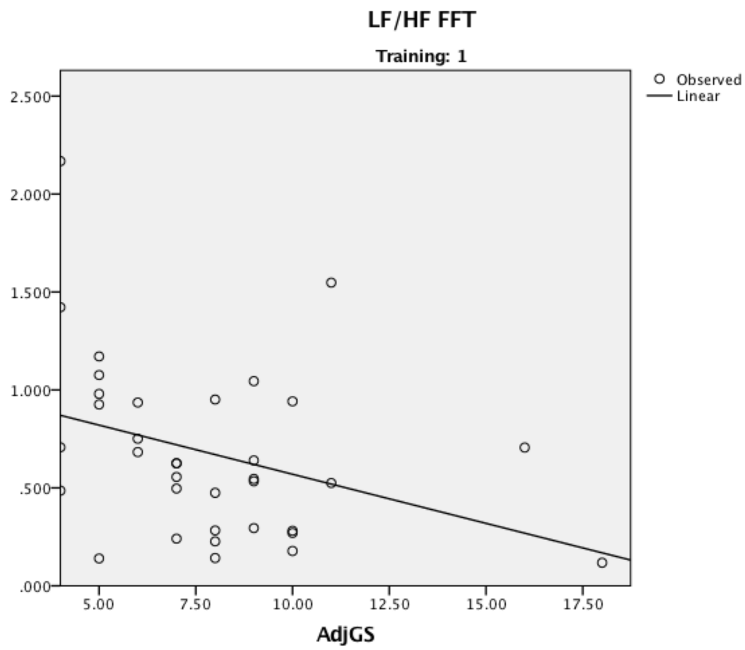


Figure 2.9: Linear regression for the Recovery-Stress Questionnaire (RESTQ) category general stress on the x-axis and the autoregressive analysis of the HRV frequency domain measure of the ratio of the low frequency to high frequency power (LF/HF AR) on the y-axis for the endurance group.

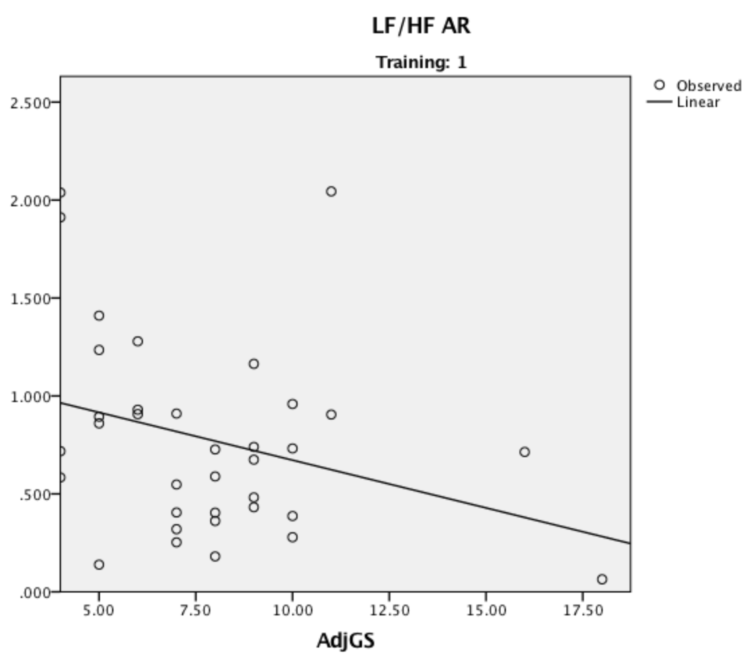


Figure 2.10: Linear regression for the Recovery-Stress Questionnaire (RESTQ) category general stress on the x-axis and the fast Fourier technique of the HRV frequency domain measure of high frequency power (HF FFT) on the y-axis for the endurance group.

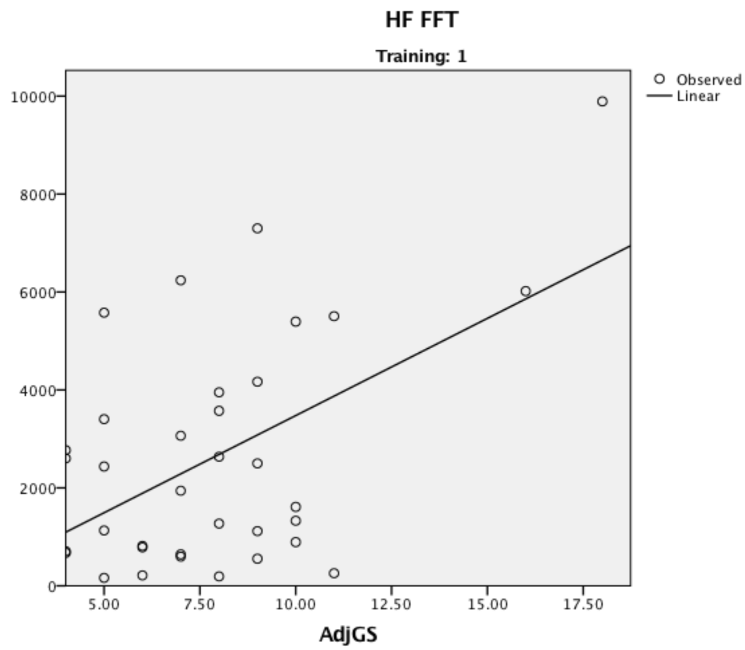
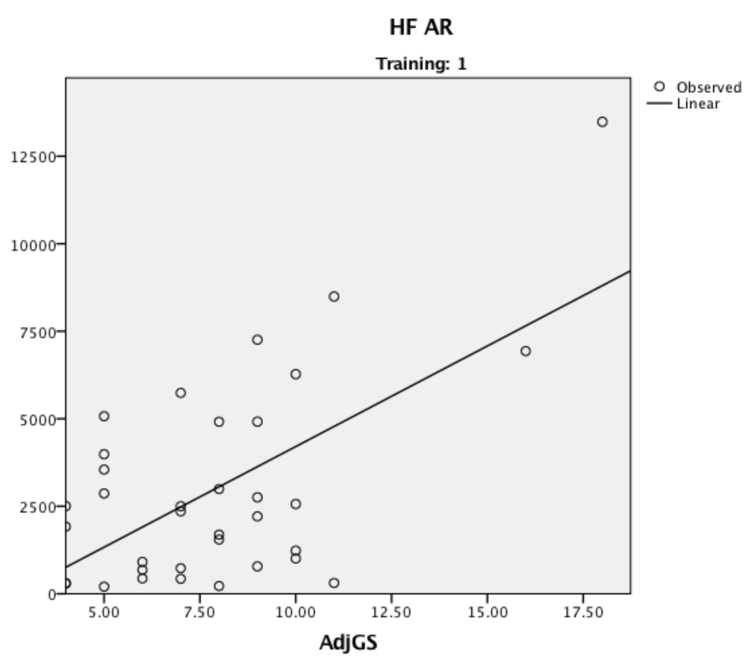


Figure 2.11: Linear regression for the Recovery-Stress Questionnaire (RESTQ) category general stress on the x-axis and the autoregressive analysis of the HRV frequency domain measure of high frequency power (HF AR) on the y-axis for the endurance group.



A quadratic model was included in the analysis, as it has been suggested to have a superior fit in analyzing HRV measures for those with bradycardia [20]. The parasympathetic HRV measures continue to increase as AcH increases until a saturation point is reached where despite increases in parasympathetic stimulation the measures will plateau, a characteristic that may not fit the linear model [10, 20]. The characteristic of the parasympathetic measures, such as HF power and RMSSD, in response to increasing parasympathetic modulation is traditionally concave down, and for sympathetic measures, such as LF/HF, in response to increasing sympathetic modulation, is traditionally concave up [20]. The curvilinear relationship between stress level and the parasympathetic measures of HRV, RMSSD and HF, was apparent with the endurance group having significant curvilinear relationships between RMSSD, HF FFT and HF AR and emotional stress, conflicts/pressures and physical complaints. There was a linear increase in HRV levels and stress score as there was sufficient stress to invoke change however as the stress increased past a certain level, the HRV levels began to decrease with the increased stress resulting in the curvilinear graph as seen in figures 2.12 to 2.17. Emotional stress (32.1%) and conflicts-pressures (32.9%) had the greatest influence on HF AR with similar levels apparent with RMSSD (30.2% and 30.7% respectively). The emotional stress and conflicts-pressures could also result in an increase in epinephrine and an increase in sympathetic modulation indicating that the changes in physiological variables may not be solely training related [59].

Figure 2.12: Curvilinear regression for the Recovery-Stress Questionnaire (RESTQ) category emotional stress on the x-axis and the HRV time domain variable root mean square of the standard deviation of RR intervals (RMSSD) on the y-axis for the endurance group.

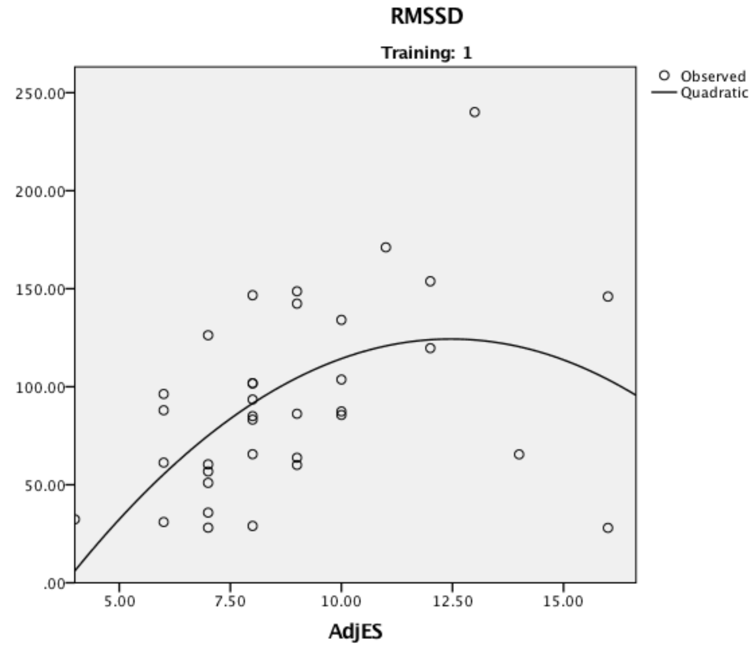


Figure 2.13: Curvilinear regression for Recovery-Stress Questionnaire (RESTQ) category emotional stress on the x-axis and the fast Fourier technique of the HRV frequency domain measure of high frequency power (HF FFT) on the y-axis for the endurance group.

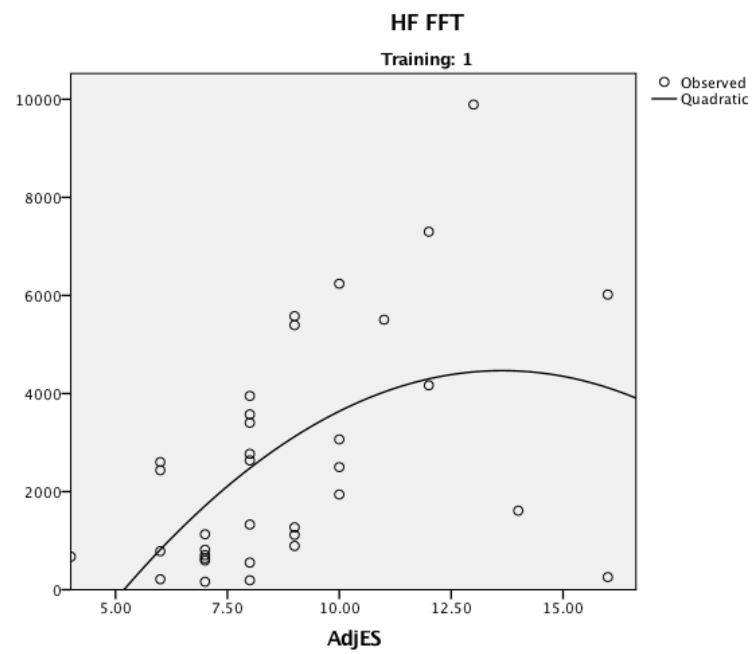


Figure 2.14: Curvilinear regression for the Recovery-Stress Questionnaire (RESTQ) category emotional stress on the x-axis and the autoregressive analysis of the HRV frequency domain measure of high frequency power (HF AR) on the y-axis for the endurance group.

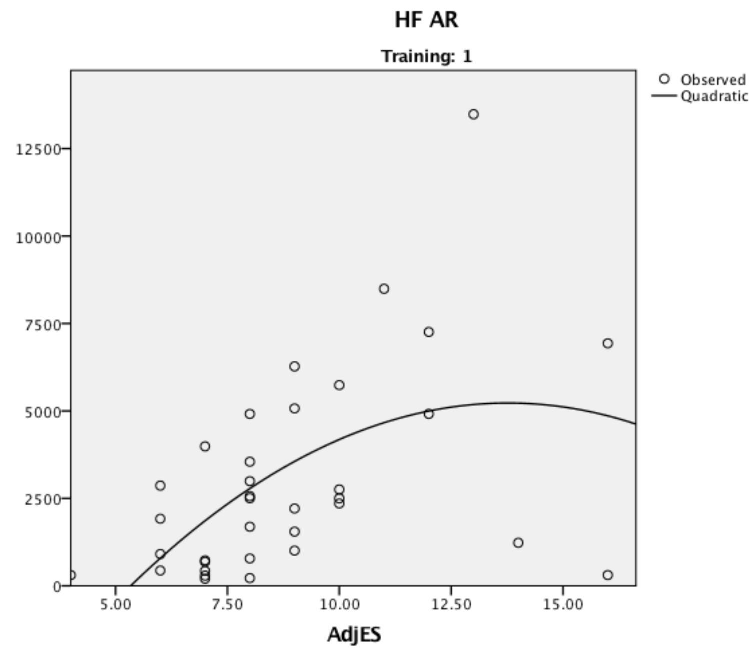


Figure 2.15: Curvilinear regression for the Recovery-Stress Questionnaire (RESTQ) category conflicts-pressures on the x-axis and the HRV time domain variable root mean square of the standard deviation of RR intervals (RMSSD) on the y-axis for the endurance group.

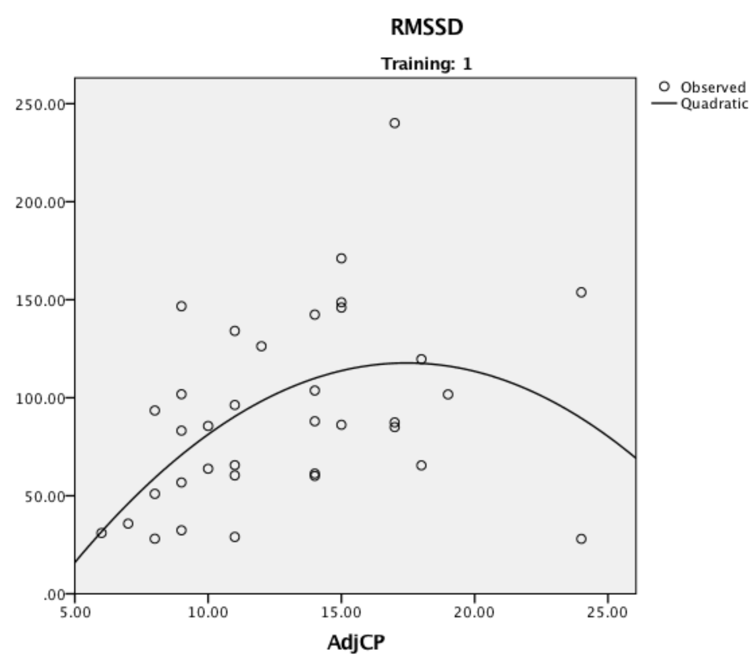


Figure 2.16: Curvilinear regression for the Recovery-Stress Questionnaire (RESTQ) category conflicts-pressures on the x-axis and the fast Fourier technique of the HRV frequency domain measure of high frequency power (HF FFT) on the y-axis for the endurance group.

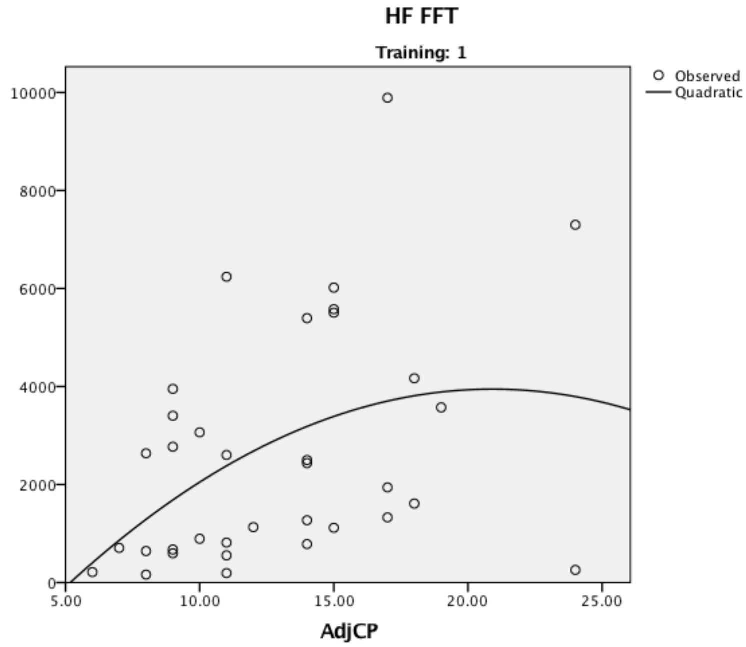
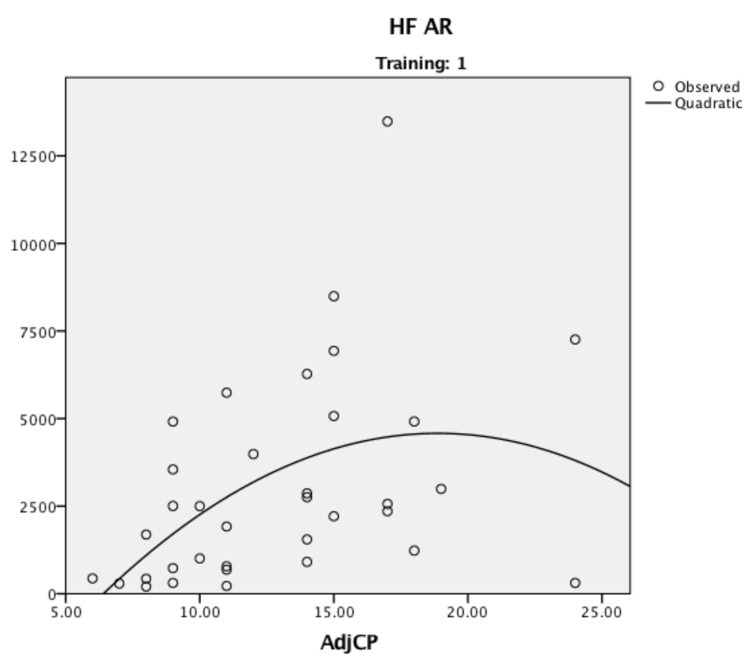


Figure 2.17: Curvilinear regression for the Recovery-Stress Questionnaire (RESTQ) category conflicts-pressures on the x-axis and the autoregressive analysis of the HRV frequency domain measure of high frequency power (HF AR) on the y-axis for the endurance group.



With just the non-endurance athletes, the RMSSD, HF FFT and HF AR had a significant curvilinear relationship with fatigue with RMSSD being accounted for by the largest amount of variation, 19.6%. The curve was concave up indicating increase in the parasympathetic HRV measure as the fatigue levels increase, which is opposite to the expected relationship. These results highlight that the subjective component and physiological component may respond differently to stress in the non-endurance athletes. One of the concerns with overreaching, a precursor to OTS, is an increase in fatigue leading to a lack of motivation to perform. Our results demonstrated that the subjective information on fatigue were not reflected in HRV measures which suggests the inclusion of both subjective and physiological measures when examining the athletes' fatigue related stress level [61]. Sleep quality, a measure of recovery, had a strong curvilinear relationship with RMSSD accounting for 22.5% of the variance in the non-endurance athletes. This was characterized by a concave up relationship with a distinct bend in the curve at where RMSSD levels increase as recovery levels increase, highlighting the influence of sleep quality on the parasympathetic modulation of HRV in college student athletes [6, 60, 62, 63].

Figure 2.18: Curvilinear regression for the Recovery-Stress Questionnaire (RESTQ) category fatigue on the x-axis and the time domain HRV measure of the root mean square of the standard deviation of the RR intervals (RMSSD) on the y-axis in the non-endurance group.

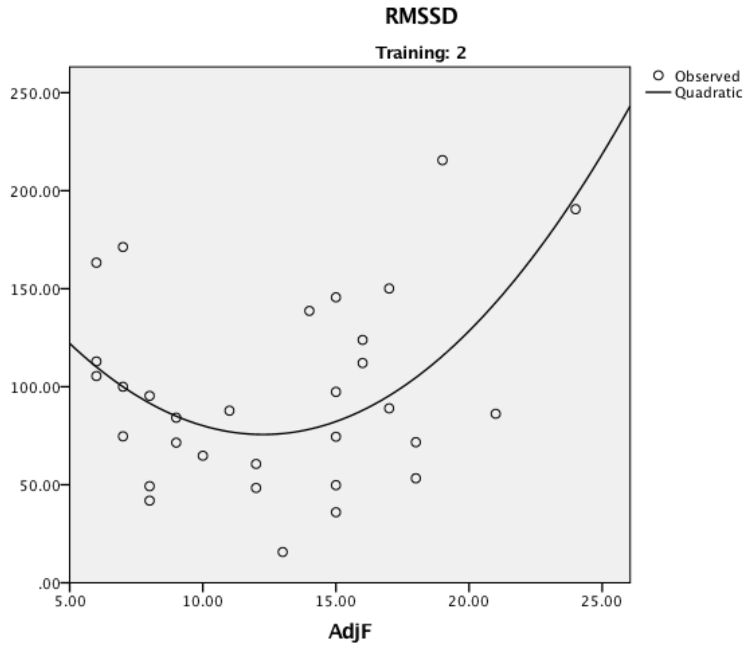


Figure 2.19: Curvilinear regression for the Recovery-Stress Questionnaire (RESTQ) category fatigue on the x-axis and the fast Fourier technique of the HRV frequency domain measure of high frequency power (HF FFT) on the y-axis for the non-endurance group.

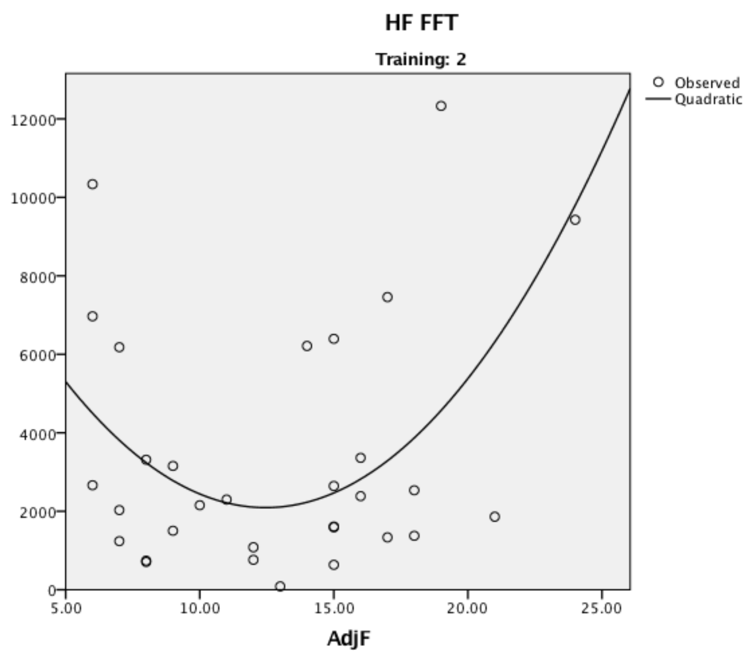


Figure 2.20: Curvilinear regression for the Recovery-Stress Questionnaire (RESTQ) category fatigue on the x-axis and the autoregressive analysis of the HRV frequency domain measure of high frequency power (HF AR) on the y-axis for the non-endurance group.

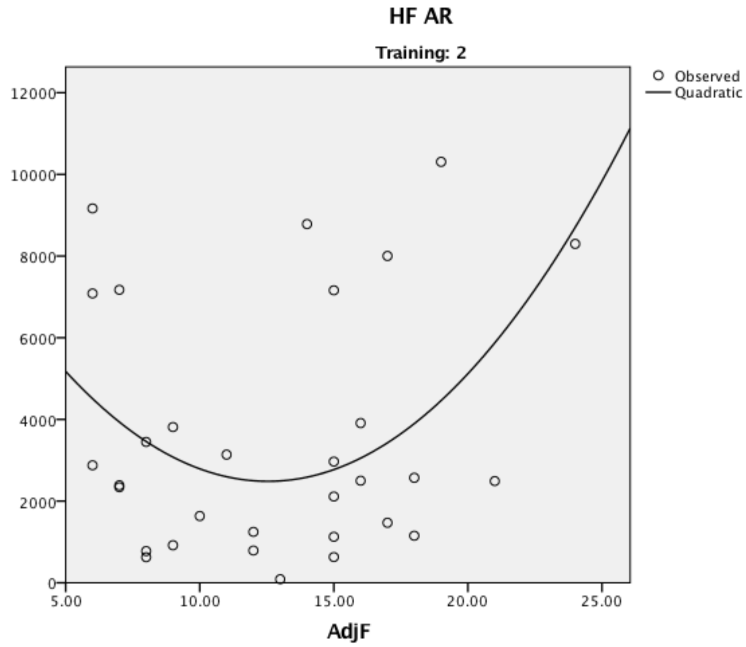
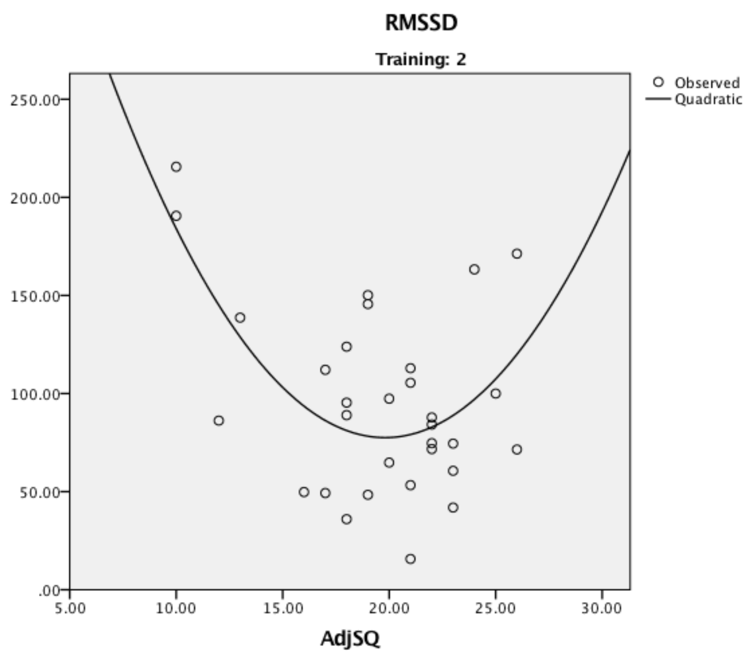


Figure 2.21: Curvilinear regression for the Recovery-Stress Questionnaire (RESTQ) category sleep quality on the x-axis and the time domain HRV measure of the root mean square of the standard deviation of the RR intervals (RMSSD) on the y-axis in the non-endurance group.



The RESTQ-Sport is purported to identify training and non-training stress and recovery via the 19 scales therefore the HRV variables of RMSSD and HF power, associated with parasympathetic modulation, were expected to have a negative linear relationship with the stress scales and a positive linear relationship with the recovery scales. The results do not always support this relationship as there were significant positive linear relationships with the stress scales and significant negative linear relationships with the recovery scales. The LF/HF ratio, presumed to measure sympathetic activity, had no significant linear relationships with any of the variables for the entire group, however when divided into the endurance and non-endurance groups there were significant negative relationships where decreased sympathetic activity was associated with increased RESTQ-Sport scores which was appropriate for the recovery scales but not for the stress scales. According to the manual for the RESTQ-Sport the general stress scale has been determined to be reflective of the individual's subjective measure of overall stress; however our data indicated that the general stress scale was not associated with any of the HRV measures in the NCAA Division I Collegiate athletes [44]. As most of the research with the RESTQ-Sport has not included football, baseball, basketball and water polo, it is possible that inclusion of these non-endurance athletes, as well as stress related to academics may have altered some of the sensitivity of the RESTQ-Sport, however it should not have influenced the HRV. In addition, the non-normal distribution of HRV variables necessitated the log transformation, a common procedure used in the literature, which may have altered the results in regards to the relationship with the RESTQ-Sport questionnaire. The need for further research into subjective monitoring to include non-training stresses for the NCAA Division I Collegiate student athlete is highlighted by the results of this study, as there was a consistent influence by most of the general non-training stress scales on HRV. Moreover, the interpretation of the RESTQ-Sport with collegiate student athletes should be taken with caution as some relationships were inverse. Additional research would be needed to determine the most appropriate combination of HRV measures and RESTQ-Sport scales in monitoring the stress and recovery levels of college student athletes over the course of the academic period and the athletic season.

Table 2.14: Full data set non-significant linear results by RESTQ-Sport Category

The heart rate (HR) variables include resting heart rate (RHR), the root mean square of the standard deviation of RR intervals (RMSSD), the ratio of low frequency to high frequency power (LF/HF) and the HF power. The LF/HF and HF are frequency domain variables analyzed using either the fast Fourier technique (FFT) and autoregressive analysis (AR). The Recovery-Stress Questionnaire for athletes (RESTQ) defines the scales of either stress or recovery.

RESTQ Category	HR Variable	R	R^2	Adjusted R^2	Sig F Change	B Variable
Emotional Stress	RHR	.340	.058	.043	.052	.007
	RMSSD	.239	.057	.042	.054	.022
	LF/HF FFT	.011	.000	-.015	.928	-.001
	LF/HF AR	.056	.003	-.012	.656	-.007
Social Stress	RHR	.166	.027	.012	.184	.004
	RMSSD	.234	.055	.040	.059	.019
	LF/HF FFT	.033	.001	-.015	.793	-.004
	LF/HF AR	.034	.001	-.014	.784	-.004
Conflicts-Pressures	RMSSD	.080	.006	-.009	.525	.005
	LF/HF FFT	.128	.016	.001	.304	-.011
	LF/HF AR	.126	.016	.000	.314	-.010
	HF FFT	.096	.009	-.006	.442	.011
	HF AR	.121	.015	-.001	.335	.014
Fatigue	RMSSD	.082	.007	-.009	.511	.004
	LF/HF FFT	.085	.007	-.008	.498	-.006
	LF/HF AR	.039	.002	-.014	.756	-.003
	HF FFT	.086	.007	-.008	.492	.008
	HF AR	.096	.009	-.006	.443	.009
Physical Complaint	RMSSD	.060	.004	-.012	.630	.004
	LF/HF FFT	.051	.003	-.013	.682	-.005
	LF/HF AR	.003	.000	-.016	.981	.000
	HF FFT	.099	.010	-006	.429	.013
	HF AR	.083	.007	-.009	.509	.011
Sleep Quality	RHR	.131	.017	.002	.294	-.002
	RMSSD	.165	.027	.012	.186	-.008
	LF/HF AR	.165	.027	.012	.186	.011
	HF FFT	.135	.018	.003	.281	-.013
	HF AR	.151	.023	.007	.228	-.014
Disturbed Breaks	RMSSD	.129	.017	.001	.302	.010
	LF/HF FFT	.062	.004	-.012	.621	-.007
	LF/HF AR	.033	.001	-.015	.791	-.004
	HF FFT	.118	.014	-.001	.343	.019
	HF AR	.123	.015	.000	.327	.020
Emotional Exhaustion	LF/HF FFT	.147	.022	.006	.240	-.013
	LF/HF AR	.139	.019	.003	.272	-.012
Injury	RMSSD	.140	.019	.004	.263	.007
	LF/HF FFT	.171	.029	.014	.170	-.013
	LF/HF AR	.071	.005	-.011	.573	-.005
	HF FFT	.144	.021	.005	.248	.014
	HF AR	.155	.024	.009	.213	.016

Table 2.15: RESTQ-Sport categories with no significant relationships for the full data set
These Recovery-Stress Questionnaire (RESTQ) scales have no significant relationship with any dependent variable for the entire data set. The heart rate (HR) variables include resting heart rate (RHR), the root mean square of the standard deviation of RR intervals (RMSSD), the ratio of low frequency to high frequency power (LF/HF) and the HF power. The LF/HF and HF are frequency domain variables analyzed using either the fast Fourier technique (FFT) and autoregressive analysis (AR). The RESTQ defines the scales of either stress or recovery.

RESTQ Category	HR Variable	R	R^2	Adjusted R^2	Sig F Change	B Variable
General Stress	RHR	.033	.001	-.015	.796	-.001
	RMSSD	.176	.031	.016	.158	.014
	LF/HF FFT	.143	.020	.005	.253	-.017
	LF/HF AR	157	.025	.009	.208	-.018
	HF FFT	.110	.012	-.003	.378	.017
	HF AR	.156	.024	.009	.211	.025
Lack of energy	RHR	.160	.026	.010	.199	.004
	RMSSD	.156	.024	.009	.210	.013
	LF/HF FFT	.007	.000	-.016	.954	.001
	LF/HF AR	.004	.000	-.016	.974	.000
	HF FFT	.119	.014	-.001	.343	.018
	HF AR	.200	.040	.025	.107	.032
Success	RHR	.269	.072	.058	*.029	.006
	RMSSD	.034	.001	-.014	.784	-.002
	LF/HF FFT	.085	.007	-.008	.498	.008
	LF/HF AR	.081	.007	-.009	.519	.008
	HF FFT	.024	.001	-.015	.848	.003
	HF AR	.029	.001	-.015	.816	.004
Social Recovery	RHR	.200	.040	.025	.108	.003
	RMSSD	.085	.007	-.008	.497	-.005
	LF/HF FFT	.232	.054	.039	.061	.018
	LF/HF AR	.234	.055	.040	.059	.018
	HF FFT	.074	.006	-.010	.553	-.008
	HF AR	.063	.004	-.012	.616	-.007
Physical Recovery	RHR	.239	.057	.042	.053	.051
	RMSSD	.228	.052	.037	.066	-.022
	LF/HF FFT	.001	.000	-.016	.996	9.308E-
	LF/HF AR	.020	.000	-.015	.871	.003
	HF FFT	.237	.056	.041	.055	-.044
	HF AR	.218	.047	.032	.081	-.041
General Well-being	RHR	.017	.000	-.015	.893	.000
	RMSSD	.129	.017	.001	.304	-.007
	LF/HF FFT	.135	.018	.003	.279	.011
	LF/HF AR	.131	.017	.002	.296	.011
	HF FFT	.131	.017	.002	.296	-.014
	HF AR	.120	.014	-.001	.338	-.013
Being in-shape	RHR	.000	.000	-.016	.998	-4.815E-6
	RMSSD	.198	.039	.024	.111	-.012

	LF/HF FFT	.144	.021	.005	.250	.013
	LF/HF AR	.129	.017	.001	.303	.011
	HF FFT	.093	.009	-.007	.460	-.011
	HF AR	.164	.027	.012	.188	-.020
Personal Accomplishment	RHR	.080	.006	-.009	.522	.002
	RMSSD	.013	.000	-.015	.919	.001
	LF/HF FFT	.115	.013	-.002	.359	-.010
	LF/HF AR	.092	.008	-.007	.464	-.008
	HF FFT	.078	.006	-.009	.535	.009
	HF AR	.034	.001	-.014	.785	.004
Self-efficacy	RHR	.026	.001	-.015	.835	.000
	RMSSD	.219	.048	.033	.077	-.013
	LF/HF FFT	.143	.021	.005	.251	.012
	LF/HF AR	.127	.016	.001	.308	.010
	HF FFT	.162	.026	.011	.194	-.018
	HF AR	.203	.041	.026	.102	-.023
Self-Regulation	RHR	.264	.070	.055	*.032	.005
	RMSSD	.032	.001	-.015	.798	-.002
	LF/HF FFT	.156	.024	.009	.212	-.013
	LF/HF AR	.115	.013	-.002	.356	-.009
	HF FFT	.003	.000	-.016	.983	.000
	HF AR	.030	.001	-.015	.809	.003

*Residuals are homoscedastic

Chapter 3

Validation of the Photoplethysmographic Technique using a Smartphone Application with an Electrocardiograph in Assessing Autonomic Nervous System Function Among Collegiate Female Athletes

INTRODUCTION

Heart Rate Variability (HRV), the ability of the heart to modulate interbeat intervals and oscillations between consecutive instantaneous heartbeats, is used as a non-invasive method of analyzing the autonomic nervous system (ANS) [1-4]. In general, parasympathetic activity leads to an influx of acetylcholine that increases the firing threshold of the sinoatrial node resulting in a decreased HR and an increase in the variability between successive R to R intervals. Conversely, sympathetic activity results the presence of epinephrine or norepinephrine leading to an increased HR and less variability between heartbeats. [3, 4] Because each branch of the ANS has different response characteristics on HR modulation, analysis of HRV is used to determine autonomic balance with electrocardiographic (ECG) recording analysis serving as the gold standard for assessing change [1, 2, 4]. Time domain measures are calculated from the interval between successive normal complexes, either as direct measures of HR or statistical measures derived from the differences in intervals to reflect variance. Common time domain measures include the standard deviation of the RR intervals (SDNN), the square root of the mean squares of successive RR intervals (RMSSD) and the proportion of successive RR intervals greater than 50ms (pNN50). [1] Frequency domain measures display how power (variance) distributes as a function of frequency where the low frequency (LF) and high frequency (HF) vary in relation to the changes in autonomic function and the very low frequency (VLF) is indicative of thermoregulatory activity [1, 3]. The sympathetic nervous system can only affect the LF components of HRV, while parasympathetic activity can modulate both the LF and HF components [2]. The ECG data is transformed into numerical data of the R to R intervals, filtered to remove ectopic beats and analyzed with HRV analysis software such as Kubios HRV software (ver. 2.1, Kuopio Finland) [1, 3].

Interest in utilizing HRV measurements as a field assessment has led to the development of smartphones applications for monitoring HRV data as an alternative to the traditional ECG lab-based data collection [64-66]. One example of smartphone technology foregoes the use of a traditional chest strap to monitor the heart's electrical activity by using an optical recording of the pulse wave, referred to as photoplethysmography (PPG), as an alternative measurement of cardiac cycles [67]. Instead of measuring changes in the electrical activity as with the ECG, PPG measures the relative blood volume changes of peripheral circulation through non-invasive pulse oximetry, based on light absorption [67, 68]. The PPG waveform consists of a direct current component that is based on a non-pulsatile blood volume that produces a slowly changing signal and an alternating current component that is attributed to the arterial pulse [68]. The same autonomic changes that influence HRV can be extracted from PPG to determine pulse rate variability (PRV), the variation between successive arterial pulse beats, with both measures highly correlated in both stationary and non-stationary conditions [67, 68]. Simultaneous analysis of ECG data and PPG shows accuracy in raw data as well as time domain and frequency domain analysis when HRV is measured during psychological tasks and basic exercise tasks, however it has not been validated at rest in athletes who have lower heart rates and increased parasympathetic activity secondary to training [30, 67].

Substituting PRV data for the traditional ECG data with the use of a smartphone provides benefits to researchers as well as to athletes and coaches [64, 67]. Current trends in training adopt the use of daily or weekly HRV changes in determining recovery from exercise [8, 69].

Most research protocols use morning HRV data collection taken within a few minutes of waking and voiding of the bladder, prior to activity, eating, drinking caffeinated beverages or using tobacco products [6, 47, 66, 70]. As most college student athletes have smartphones with a camera and flash component, the use of an application that has compatible technology provides a convenient method for daily HRV monitoring [66, 71]. In order for this technology to be useful, it must be validated against the gold standard ECG recording for this population [64, 67].

Therefore the purpose of this study was to test the reliability of the smartphone application against HRV data collected simultaneously from resting ECG data. It was hypothesized that the smartphone application data would not be significantly different from the traditional ECG laboratory based data and that the smartphone application R-R intervals would not be significantly different from the ECG R-R intervals.

METHODS

Research Design

This study employed a cross-sectional design to validate the smartphone application against the gold standard ECG. All participants underwent one resting data collection session. The time domain measure of RMSSD, SDNN and pNN50 and the fast Fourier transformation (FFT) frequency domain measure of LF peak, HF peak and LF/HF ratio were used as the HRV outcome measure, which was compared between data collected via the ECG data collection and the smartphone application, using the capability of the application to measure R to R intervals and to produce its own time domain and frequency domain measures. The three measurements of data compared were: the R-R intervals collected via the ECG and analyzed using Kubios software (ECG-Kubios), the R-R intervals collected via the smartphone application and analyzed using Kubios software (smartphone-Kubios) and via the smartphone application output (smartphone-output).

Cross-sectional data collection

Participants

Thirty-two female participants (mean age = 19.3±0.95 years, mean ECG RHR =52±9) training with NCAA Division I athletic teams were recruited. Prior to inclusion in the study, participants filled out Health History Questionnaire and informed consent form approved by the University of Hawaii Human Study Program. Participants that self-identify in the health history questionnaires as having an allergy to adhesives or suspected pregnancy were not eligible for inclusion in this study.

Table 3.1: Descriptive Statistics: Descriptive statistics presented for the 32 female NCAA Division I Collegiate athletes including age, height, body mass and resting heart rate (RHR).

N=32 female	Mean±SD
Age (yrs)	19.30±0.92
Height (m)	1.67±0.08
Body Mass (kg)	60.29±10.54
RHR (bpm)	52.24±9.4

Instruments

The ECG data was collected using CARDIO-CARD^{TM} ver. 6.01ia software (Nasiff Associates, Inc., Brewerton, NY, USA). Anthropometric data including height (cm) measured by wall-mounted stadiometer, body mass (kg) measured by Detecto Certifier scale (Detecto, Webb City, MO, USA) and age were collected and plugged into the CARDIO-CARD^{TM}. Prior to electrode application, the skin was cleaned and prepped. The right and left arm electrodes were placed below the right and left clavicles, respectively. The right and left leg electrodes were attached to the right and left sides of the trunk, below the tenth rib on the anterior axillary line. The V5 chest electrode was placed on the left side of the fifth intercostal space on the anterior axillary line. Additional HRV data collection occurred simultaneously by a smartphone using the Camera HRV iPhone application ver 4.5.7. This application allowed for the recording both time domain and frequency domain measures using PPG, a technique that detects changes in blood volume during the cardiac cycle by illuminating the skin and measuring changes in light absorption [68, 72]. CardioCard™ converts the ECG data into a comma separated value (.csv) file of the time in milliseconds between consecutive R to R intervals. The smartphone application also converts the PPG data into a .csv file of the time in milliseconds between consecutive R to R intervals. To obtain time and frequency domain measures, the ECG and PRV RR interval data were then exported to reliable software for calculating HRV measures, Kubios Heart Rate Variability ver. 2.1 software (Biosignal Analysis and Medical Imaging Group, Dept. of Physics, University of Kuopio, Finland) [3]. The smartphone application produces its own calculations of time and frequency domain HRV measures which are stored in the phone in one to five minute intervals and can be exported as an Excel file. The smartphone application was set to store the data in approximately one minute intervals for ease of extrapolating the resting data from the fifteen minute data collection. The Kubios analysis of the ECG R to R interval data (ECG-Kubios) was compared to the smartphone R to R interval data (smartphone-Kubios) to determine if both methods of data collection could produce similar results when analyzed via the heart rate variability software. Both the ECG-Kubios and the smartphone-Kubios data were then compared against the smartphone-output to determine if the smartphone calculations produced similar results to the software.

Experimental Procedures

The testing sessions were conducted in the Human Performance Laboratory at the University of Hawaii at Manoa. Participants were asked to refrain from any vigorous activities, such as playing sports and riding bicycle as well as ingesting any caffeine, 3 hours prior to the data collection. Following the verbal explanation of the study procedure, all participants were asked to sign an informed consent form and fill out the Health History Questionnaire to identify exclusionary criteria.

A Board of Certification Certified Athletic Trainer collected all laboratory data. Anthropometric data were collected and recorded prior to the testing session. Following anthropometric measurements, the participant was instructed to lie down supine or semi-reclined in a comfortable position in which they could remain throughout the data collection. The investigator cleaned the electrode placement sites and the electrodes were applied to designated positions. The participant’s hand was placed comfortably with one finger over the flash for the smartphone application collection. After 10 minutes of resting in comfortable position, the ECG and PRV were recorded for 15 minutes. The participant was instructed to relax and breathe at their normal, self-determined pace, remain as steady as possible, and not to fall asleep during the data collection period.

Following the data collection procedure, raw R to R interval data from the ECG and the smartphone application were used to calculate HRV. The R to R intervals were visually inspected to remove any ectopic beats and insure that high T-waves were not mistaken for an R-wave. The filtered data were exported into Kubios Heart Rate Variability Software Version 2.0 (University of Kuopio, Kuopio, Finland) to assess time and frequency domain measures based on the recommendations set forth by the Task Force. Data was smoothed using the low-level artifact correction and trend components were removed using a Smooth n Priors to remove the influence of the VLF and filter any artifact. Frequency bands for HRV analysis were set as follows: VLF (0-0.04 Hz), LF (0.04-0.15 Hz), and HF (0.15-0.4 Hz). Interpolation of the interbeat intervals (RR series) was set at 4 Hz. Window width for fast Fourier transformation was set at 256 seconds with the window overlap set at 50%. [1] In the Kubios software, the most stable five minute data period of ECG R to R interval data was selected for analysis. The same five minute curve was then matched in Kubios for the smartphone application R to R interval data. Because the smartphone-output does not produce a curve, the ECG-Kubios output time was matched to the nearest minute on the excel spreadsheet from the smartphone-output and averaged for five minutes.

Statistical Analysis

The SPSS version 24 with a significance level set at $p<0.05$ was used for all statistical analyses (IBM Inc., Chicago, IL). Descriptive statistics were calculated for each subject.

A one-way analysis of variance (ANOVA) and Pearson product correlation were used to validate the smartphone-output against the smartphone-Kubios and the ECG-Kubios. Means and standard deviations were calculated for the time domain measures of SDNN, RMSSD and pNN50 and the FFT frequency domain measures of LF peak, HF peak, and LF/HF as calculated by Kubios Heart Rate Variability software for the same five minute period of data collected via ECG recording and the RR intervals collected by the smartphone application. In addition, effect size was calculated as the same participants were used for all three measures. The same five minute period was closely matched to the data output collected by the smartphone application. The Inter-Class Correlations (ICC) using the ICC (1,1) as outlined by Shrout and Fleiss with the appropriate standard error of the measurement (SEM) and Bland-Altman plots were calculated with limits of agreement reported [31, 32]. Linear regression analysis was used as a diagnostic procedure to determine if there was any proportional bias between the residuals [32].

Table 3.2: Analysis of Variance comparing the ECG and Smartphone data analyses
Analysis of Variance (ANOVA) comparing the time domain HRV measures standard deviation of NN intervals (SDNN), root mean square of the standard deviation of NN intervals (RMSSD) and proportion of successive NN intervals greater than 50 (pNN50) and the fast Fourier transformation frequency domain HRV measures of low frequency peak (LF), high frequency peak (HF) and ratio of low frequency to high frequency (LF/HF) for the three conditions, smartphone-Kubios, smartphone-output and ECG-Kubios. The time domain measures are not significantly different between the three measures.

	N	Smartphone-Kubios (Mean±SD)	Smartphone-output (Mean±SD)	ECG-Kubios (Mean±SD)	F	Sig	η_p^2
SDNN (ms)	32	75.55±24.64	78.68±23.59	69.76±31.99	.899	.411	.019
RMSSD (ms)	32	99.71±35.21	94.19±32.96	91.22±43.20	.424	.655	.009
pNN50 (%)	32	52.99±19.50	50.78±20.16	46.48±23.16	.795	.455	.017
LF (ms$^{2)}$	32	.109±.027	.079±.057	.101±.030	4.550	.013*	.089
HF (ms^2)	32	.232±.048	.071±.056	.222±.056	92.279	.000**	.665
LF/HF	32	.755±.451	1.421±.562	.963±.587	20.827	.000**	.309

*. Significant at the 0.05 level.
**. Significant at the 0.001 level.

RESULTS

A one-way ANOVA (table 3.2) between the ECG-Kubios data, the smartphone-Kubios and the smartphone-output indicated no difference between the time domain measures of SDNN ($F(2,93)$ =.899, p=.411, η_p^2= .019**),** RMSSD ($F(2,93)$ = .424, p=.655, η_p^2= .009) and pNN50 ($F(2,93)$ =.795, p=.455, η_p^2= .017). There were differences for the frequency domain measures of LF peak ($F(2,93)$ = 4.550, p=.013, η_p^2= .089), HF peak ($F(2,93)$ = 92.279, p<.001, η_p^2= .665) and LF/HF ($F(2,93) = 20.827$, $p<.001$, $\eta_p^2 = .309$). Post hoc analysis using Least Significant Difference indicated that the frequency domain measures were significantly different between the calculations obtained via Kubios and the calculations done by the smartphone application. The LF power measures were significantly different for the smartphone-output data compared to the ECG-Kubios ($p=.035$) and the smartphone-Kubios data ($p=.005$). The HF power measures were significantly different for the smartphone-output data compared to the ECG-Kubios ($p<.001$) and the smartphone-Kubios data ($p<.001$). The LF/HF ratio measures were significantly different for the smartphone-output data compared to the ECG-Kubios ($p<.001$) and the smartphone-Kubios ($p<.001$). There was no significant difference between the ECG-Kubios or the smartphone-Kubios (table 3.3).

Table 3.3: Least Squares Differences Post-Hoc Analysis

Post-Hoc Analysis was performed using the Least Squares Difference comparing the time domain HRV measures standard deviation of NN intervals (SDNN), root mean square of the standard deviation of NN intervals (RMSSD) and proportion of successive NN intervals greater than 50 (pNN50) and the fast Fourier transformation frequency domain HRV measures of low frequency peak (LF), high frequency peak (HF) and ratio of low frequency to high frequency (LF/HF) for the three conditions, smartphone-Kubios, smartphone-output and ECG-Kubios. The frequency domain measures were significantly different between the smartphone-output and the ECG-Kubios and smartphone-Kubios. The smartphone-Kubios and ECG-Kubios data was not significantly different.

	Smartphone-Kubios vs Smartphone-output (mean±SD)	Sig	Smartphone-Kubios vs ECG-Kubios (mean±SD)	Sig	Smartphone-output vs ECG-Kubios (mean±SD)	Sig
SDNN (ms)	-3.131±6.750	.644	5.7875±6.750	.393	8.919±6.750	.190
RMSSD (ms)	5.512±9.346	.577	8.484±9.346	.366	2.972±9.346	.751
pNN50 (ms)	2.204±5.251	.676	6.509±5.251	.218	4.305±5.251	.414
LF (ms^2)	.029±.010	.005*	.008±.010	.453	-.022±.010	.035*
HF (ms^2)	.162±.013	.000**	.010±.013	.471	-.152±.013	.000**
LF/HF	-.666±.123	.000**	.042±.123	.732	.709±.123	.000**
*. The mean difference is significant at the 0.05 level.						
**. The mean difference is significant at the 0.001 level.						

There correlations between the time domain measures for all of the analyses were strong and significant (p<.001). The smartphone-Kubios and the smartphone-output data showed the strongest correlations. The correlations were significant for the frequency domain measures when comparing the smartphone-Kubios and the ECG-Kubios analysis but were not significant when the smartphone application was compared to the smartphone-Kubios or the ECG-Kubios (table 3.4).

Table 3.4: Pearson's Product Correlations comparing the ECG and Smartphone data analyses

The Pearson's Product Correlation comparing between the three conditions, smartphone-Kubios, smartphone-output and ECG-Kubios for the time domain HRV measures standard deviation of NN intervals (SDNN), root mean square of the standard deviation of NN intervals (RMSSD) and proportion of successive NN intervals greater than 50 (pNN50) and the fast Fourier transformation frequency domain HRV measures of low frequency peak (LF), high frequency peak (HF) and ratio of low frequency to high frequency (LF/HF).

	Correlation	Significance
Smartphone-Kubios SDNN vs Smartphone-output SDNN	.876	.000**
Smartphone-Kubios SDNN vs ECG-Kubios SDNN	.638	.000**
Smartphone-output SDNN vs ECG-Kubios SDNN	.721	.000**
Smartphone-Kubios RMSSD vs Smartphone-output RMSSD	.935	.000**
Smartphone-Kubios RMSSD vs ECG-Kubios RMSSD	.605	.000**
Smartphone-output RMSSD - ECG-Kubios RMSSD	.600	.000**
Smartphone-Kubios pNN50 vs Smartphone-output pNN50	.975	.000**
Smartphone-Kubios pNN50 vs ECG-Kubios pNN50	.778	.000**
Smartphone-Output pNN50 vs ECG-Kubios pNN50	.778	.000**
Smartphone-Kubios LF vs Smartphone-output LF	.279	.123
Smartphone-Kubios LF vs ECG-Kubios LF	.495	.004**
Smartphone-output LF vs ECG-Kubios LF	.185	.123
Smartphone-Kubios HF vs Smartphone-output HF	-.051	.781
Smartphone-Kubios HF vs ECG-Kubios HF	.589	.000**
Smartphone-output HF vs ECG-Kubios HF	.010	.956
Smartphone-Kubios LF/HF vs Smartphone-output LF/HF	.059	.747
Smartphone-Kubios LF/HF vs ECG-Kubios LF/HF	.710	.000**
Smartphone-output LF/HF vs ECG-Kubios LF/HF	.100	.587
**. The mean difference is significant at the 0.01 level.		

Table 3.5: ICC and SEM Comparing the ECG and Smartphone data analysis
The intraclass correlations and the standard error of the measurement comparing between the three conditions, smartphone-Kubios, smartphone-output and ECG-Kubios for the time domain HRV measures standard deviation of NN intervals (SDNN), root mean square of the standard deviation of NN intervals (RMSSD) and proportion of successive NN intervals greater than 50 (pNN50) and the fast Fourier transformation frequency domain HRV measures of low frequency peak (LF), high frequency peak (HF) and ratio of low frequency to high frequency (LF/HF).

	ICC	SEM
Smartphone-Kubios SDNN vs Smartphone-output SDNN	.871	9.69
Smartphone-Kubios SDNN vs ECG-Kubios SDNN	.610	16.84
Smartphone-output SDNN vs ECG-Kubios SDNN	.655	15.84
Smartphone-Kubios RMSSD vs Smartphone-output RMSSD	.922	10.38
Smartphone-Kubios RMSSD vs ECG-Kubios RMSSD	.584	23.97
Smartphone-output RMSSD - ECG-Kubios RMSSD	.587	23.88
Smartphone-Kubios pNN50 vs Smartphone-output pNN50	.969	3.69
Smartphone-Kubios pNN50 vs ECG-Kubios pNN50	.733	10.83
Smartphone-Output pNN50 vs ECG-Kubios pNN50	.760	10.27
Smartphone-Kubios LF vs Smartphone-output LF	.110	0.04
Smartphone-Kubios LF vs ECG-Kubios LF	.478	0.03
Smartphone-output LF vs ECG-Kubios LF	.104	0.04
Smartphone-Kubios HF vs Smartphone-output HF	-.719	0.12
Smartphone-Kubios HF vs ECG-Kubios HF	.579	0.06
Smartphone-output HF vs ECG-Kubios HF	-.643	0.12
Smartphone-Kubios LF/HF vs Smartphone-output LF/HF	-.251	0.66
Smartphone-Kubios LF/HF vs ECG-Kubios LF/HF	.714	0.31
Smartphone-output LF/HF vs ECG-Kubios LF/HF	-.250	0.66

There was a high degree of reliability with the time domain variables. Between the smartphone-Kubios and the smartphone-output, there was a high degree of reliability for SDNN (ICC = .871, SEM = 9.69), RMSSD (ICC = .922, SEM =10.38) and pNN50 (ICC=.969, SEM = 3.69). Between the smartphone-output and ECG-Kubios, the reliability was not as strong for the SDNN (ICC = .655, SEM = 15.84), RMSSD (ICC = .587, SEM = 23.88) and pNN50 (ICC = .760, SEM = 10.27) however this reliability was similar when the smartphone-Kubios was compared to the ECG-Kubios for the SDNN (ICC = .610, SEM = 16.84), RMSSD (ICC = .584, SEM = 23.97) and pNN50 (ICC = .733, SEM = 10.83). The frequency domain variables did not have a high degree of reliability between the smartphone-output and the smartphone-Kubios or ECG-Kubios (table 3.5).

In regards to the time domain variables, the Bland Altman plot shows there was one outlier from the limits of agreement of the SDNN between the smartphone-Kubios and the smartphone-output (figure 3.1) however the means were not statistically significant (p=.385). There was proportional bias as seen by the significance (p=.034) in the linear regression analysis of SDNN data between the smartphone-Kubios and ECG-Kubios (figure 3.2), indicating that the methods do not agree equally throughout the range of measurements. A log transformation of the data was done in an attempt to resolve the proportional bias, however this still did not resolve. There were two outliers from the limits of agreement for the RMSSD between the smartphone-Kubios and the ECG-Kubios (figure 3.3) however the means were not statistically significant (p=.082). For the RMSSD, between the smartphone-output and the ECG-Kubios (figure 3.4) there were three outliers and the means were not statistically significant (p=.063). There were two outliers from the limits of agreement for pNN50 between the smartphone-output and the ECG-Kubios (figure 3.5), however the means were not statistically significant (p=.089).

For the frequency domain variables, a Bland Altman plot (figure 3.6) showed three outliers from the limits of agreement for the LF peak between the smartphone-Kubios and the ECG-Kubios however the means were not statistically significant (p=.334). Bland Altman plots (Figures 3.7 and 3.8) of the smartphone-Kubios and the ECG-Kubios of HF peak (p=.220) and the LF/HF (p=.667) had two outliers from the limits of agreement.

Figure 3.1: Bland-Altman plot assessing the limits of agreement for the time domain measure of the standard deviation of successive NN intervals (SDNN) between the smartphone-Kubios and the smartphone-output. Based on linear regression of the residuals there was not significant difference (*p*=.385).

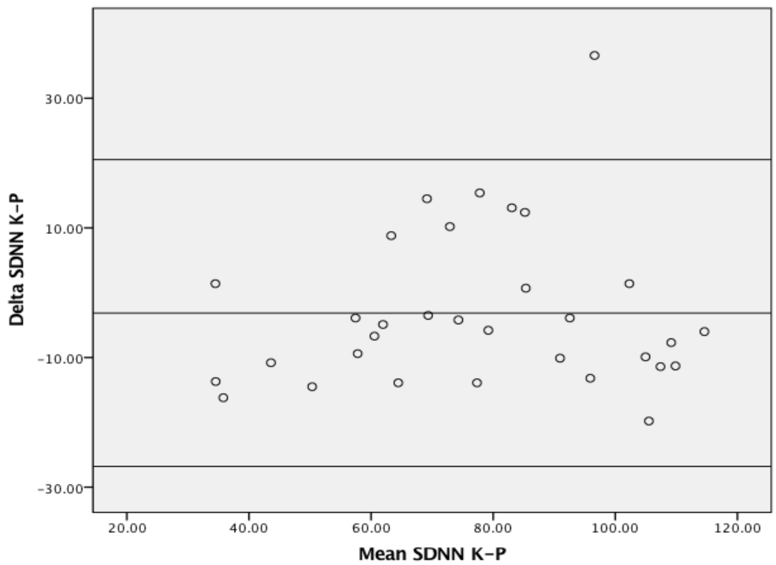


Figure 3.2: Bland-Altman plot assessing the limits of agreement for the standard deviation of NN intervals (SDNN) between the smartphone-Kubios and the ECG-Kubios. Linear regression of the residuals showed a significant difference indicating a proportional bias in the measurements (*p*=.034).

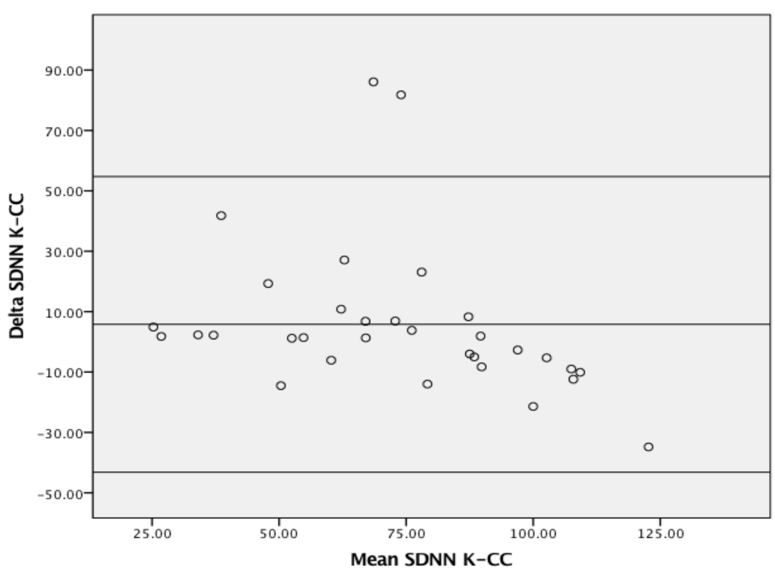


Figure 3.3: Bland-Altman plot assessing the limits of agreement for the root mean square of the standard deviation of NN intervals (RMSSD) between the smartphone-Kubios and the ECG-Kubios. Based on linear regression of the residuals there was not significant difference (p=.082).

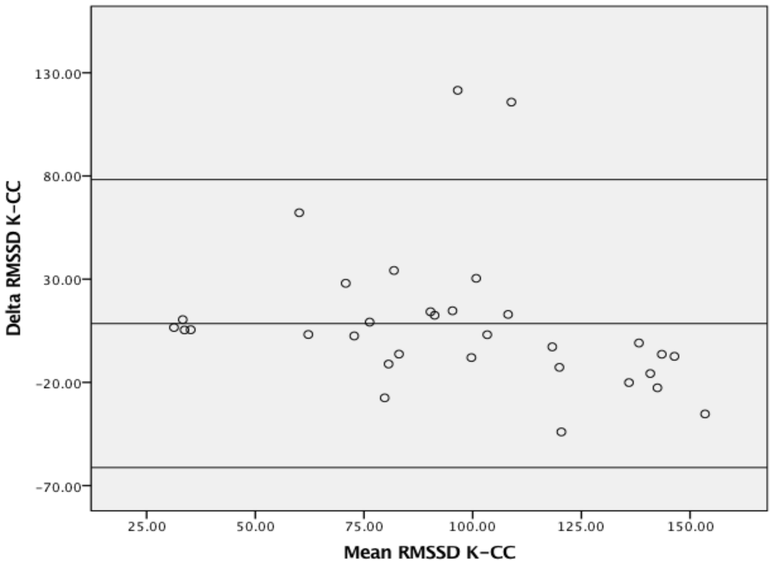


Figure 3.4: Bland-Altman plot assessing the limits of agreement for the root mean square of the standard deviation of NN intervals (RMSSD) between the the smartphone-output and the ECG-Kubios. Based on linear regression of the residuals there was not significant difference (p=.063).

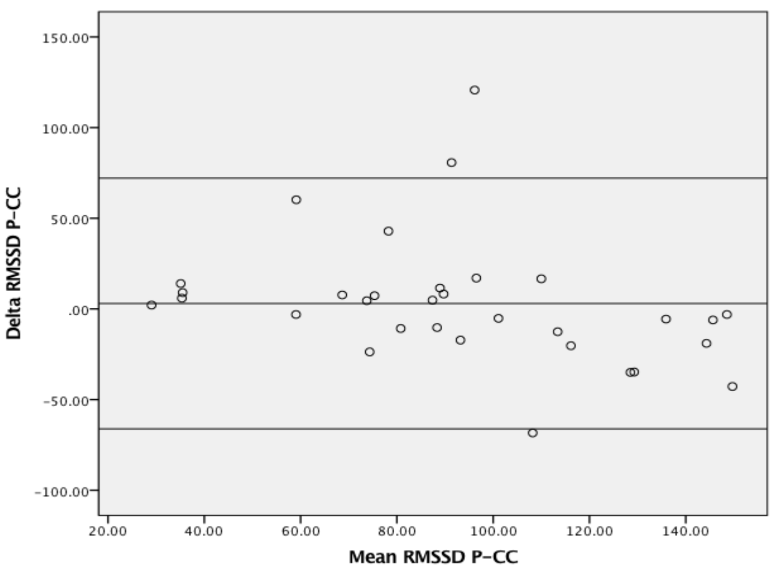


Figure 3.5: Bland-Altman plot assessing the limits of agreement for the proportion of NN intervals over 50 (pNN50) between the smartphone-output and the ECG-Kubios. Based on linear regression of the residuals there was not significant difference (*p*=.089).

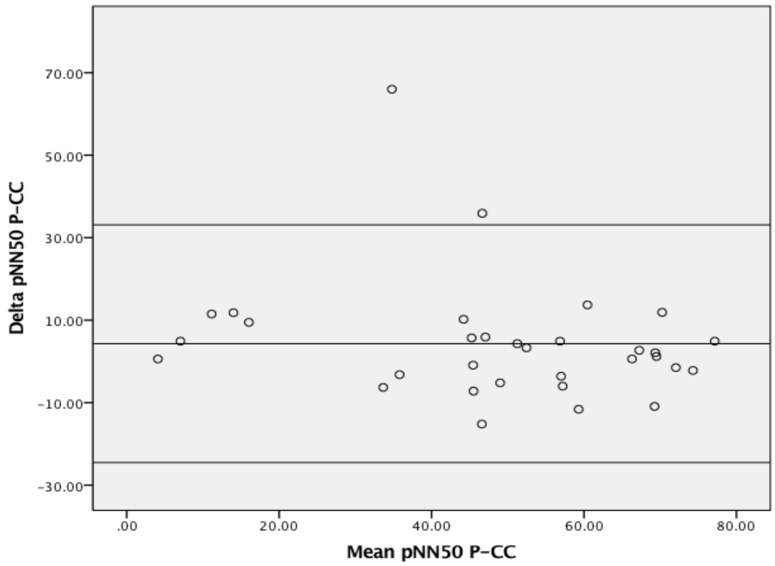


Figure 3.6: Bland-Altman plot assessing the limits of agreement for the proportion of NN intervals over 50 (pNN50) between the smartphone-Kubios and the ECG-Kubios. Based on linear regression of the residuals there was not significant difference (*p*=.334).

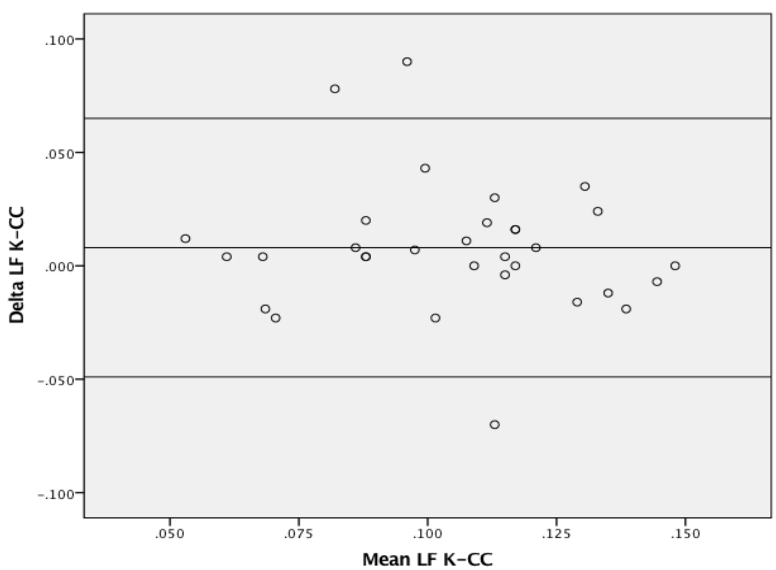


Figure 3.7: Bland-Altman plot assessing the limits of agreement for frequency domain measure of high frequency peak (HF) between the smartphone-Kubios and the ECG-Kubios. Based on linear regression of the residuals there was not significant difference (p=.220).

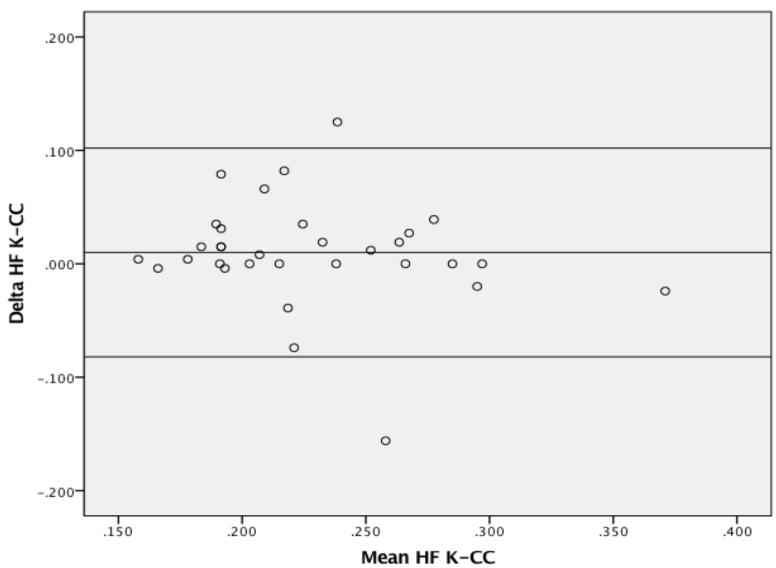
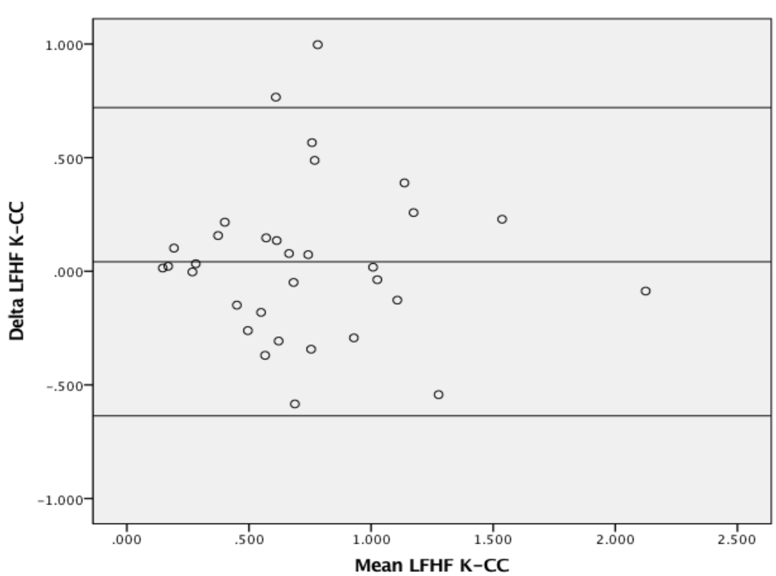


Figure 3.8: Bland-Altman plot assessing the limits of agreement for the frequency domain measure of the ratio of the low frequency to high frequency (LF/HF) between the smartphone-Kubios and the ECG-Kubios. Based on linear regression of the residuals there was not significant difference (p=.667).



DISCUSSION

Resting time domain measures were not statistically different between the ECG-Kubios (Kubios analysis of R to R intervals obtained via a standard 5-lead ECG), smartphone-Kubios (Kubios analysis of R to R intervals obtained via PPG from a the rear-facing camera flash of a smartphone), and the smartphone-output (HRV calculations made via the smartphone application made from the R to R intervals), making the PRV data collection a valid substitute for ECG data collection when time domain variables are of interest. Further analysis using ICC and Bland-Altman plots showed strong relationships and no significant differences between the means for the three measures. The ECG data is considered the gold standard because the clear waveform allows the ability to exclude data not originating from the SA node and the five lead set-up allowed the researchers to choose the clearest waveform for analysis [1]. The PRV has a short delay in the time it takes for the signal to travel from the heart to the arteries in the finger that can overestimate the length of proportionally long heart rate periods as seen in highly trained athletes, which may account for the lower strength in the correlations between the smartphone-Kubios and ECG-Kubios measures, although there was no significant difference in the correlation or the ANOVA results [67, 68, 72]. In addition, athletes with bradycardia will have a higher firing threshold of the sinoatrial node resulting in the high T-waves in the ECG data which required filtering to correct for T-waves being incorrectly identified as the QRS complex [1]. While care was taken to preserve the integrity of the data, it is possible that intervals were added incorrectly or inadvertently deleted leading to unmatched data sets. On the other hand, the smartphone application default setting automatically corrected for artifacts due to ectopic beats or motion with an RR interval correction set to 20% where any successive interval that is greater than 20% of the previous interval is removed. The stronger correlation between the time domain measures taken via the smartphone-output and the smartphone-Kubios are most likely because they come from the same RR interval series however because the time could not be synched exactly, the correlation was not perfect. The decreased level of agreement between the SDNN measures for the smartphone-Kubios and the ECG-Kubios data are most likely due to a combination of the delay in PRV signal, the inability to synch the time for the smartphone-output to Kubios and the filtering of the ECG data as these methodological concerns can lead to discrepancies in the data [1, 67, 72]. The correlations between the smartphone-output and the ECG-Kubios were not as high as the data published on the developers website, r=.98 for SDNN, r=.78 for RMSSD and r=.87 for pNN50 however the developer compared the phone to ECG data collected via a chest strap polar heart rate monitor with blue tooth capability, not the five lead ECG data collection used in this methodology and no indication was given as to the population or the number of participants for the data [http://www.marcoaltini.com/blog/heart-rate-variability]. The preferred parasympathetic measure for daily HRV analysis in athletes is RMSSD, as it remains consistent even when high levels of acetylcholine as found with bradycardia can lead to diminished levels of HF power, the frequency domain measure associated with parasympathetic modulation [8, 20]. The RMSSD has previously shown strong agreement between ECG data collection and simultaneous smartphone derived ECG measures (r=.99, for the iThlete using a chest strap, r=.92 for the Elite HRV smartphone application using a chest strap) or PRV measures ($r \geq .99$ for 9 of 10 series for the iThlete finger sensor); however the agreement is not as strong in this data set [64, 67]. The strong agreement between the time domain results from the data of these three data sets would allow some comparisons to be made between studies using five minutes of resting data from this smartphone application and an ECG recording.

The differences between the frequency domain measures of LF peak, HF peak, and LF/HF were statistically significant between the measures produced by Kubios and the smartphone application perhaps as a result of differing calculations. According to the manufacturer, the PRV data were analyzed using fast Fourier Transformation (FFT) with the frequency bands for LF (0.04-0.15Hz) and HF (0.15-0.40Hz) set to the same levels as with the analysis of the ECG -Kubios and the smartphone-Kubios. There was no indication that VLF (<0.04Hz) was included in calculations by the smartphone application. The smartphone application calculation involved linear interpolation of the RR intervals, then applying a hamming window before frequency analysis with FFT. The lack of agreement between frequency domain results is similar to what has been seen in other studies that compare different methodologies of calculating HRV data, including systematic reviews [67, 73, 74]. Caution is advised when comparing frequency domain data from studies using different software for calculations, thereby making direct comparisons of HRV data limited [74]. However the majority of HRV research utilizes Kubios Heart Rate Variability Software with standard methodologies therefore as there was no significant difference for the time domain and frequency domain measures with either the smartphone-Kubios or ECG-Kubios data in this study, analysis of the PRV intervals by Kubios would be acceptable for comparison to ECG data.

From a methodological standpoint, it was important that the analyses matched the time frame of the most stable period as closely as possible [1]. Kubios software allows for matches to be made to the exact time period, however the ECG data and the smartphone data were rarely started simultaneously resulting in a delay that was accounted for via matching the curve [73]. The removal of ectopic beats from the ECG data was accomplished by visual inspection while the PRV data was automatically filtered by the application potentially resulting in unmatched time frames. Additionally the output for the smartphone, while set up to provide analysis in one minute intervals, often gave intervals differing time lengths, up to 120 seconds apart, and without the ability to match curves as with the Kubios analysis of the data may have resulted in differing time frames that could not be adjusted [1, 73]. Caution was taken to match the time frame as close as possible between the Kubios output and the smartphone spreadsheet but they could not be matched to the exact second. This may have accounted for some of the error in the time domain variables however the frequency domain differences are most likely due to the differences in calculations.

Smartphone applications allow for ease of data collection of RR intervals for research and for HRV monitoring of training and recovery. The close limits of agreement and lack of significant difference between the time domain measures for the ECG-Kubios, smartphone-Kubios and smartphone-output make the use of this smartphone application acceptable for data collection. The frequency domain measures as calculated by the smartphone application, however, do not show strong agreement and are significantly different from both the ECG-Kubios and smartphone-Kubios measures and therefore the use of the application for these measures is questionable. As HRV monitoring relies on repeated measures from the same subject, as long as the same instrument is used for data collection and the participant collects data in the same manner every time, the amount of error can be limited and the differences can be attributed to the normal fluctuations in HRV. Comparisons cannot be made between the frequency domain measures obtained via differing software and for best results the same method of data collection and analysis should be used to ensure the least amount of error.

Chapter 4

Identifying Appropriate Statistical Measures for Calculating the Daily Change in HRV in NCAA Division I Collegiate Football Players during Off-season Conditioning

INTRODUCTION

Current trends in training involve the use of daily heart rate variability (HRV) measurements as a means for determining the effectiveness of training and to examine the cumulative effects of training stress on the autonomic nervous system (ANS) [7, 8, 69, 75]. Athletes can use daily HRV measurements and training load, calculated as the length of training multiplied by the rating of perceive exertion (RPE), to examine the effects from the previous day's training [69, 76]. Heart Rate Variability is a non-invasive method for evaluating the ANS where an increase in variation of the beat to beat intervals represents an increase in parasympathetic activity and a more steady rhythmic HR represents an increase in sympathetic activity [1, 2]. The time domain measure of root mean square of the standard deviation (RMSSD), a statistical measure of the rate between the peaks of successive QRS complexes (R-R intervals) displays the mathematical variance in HR and is the preferred measure of HRV for athletes who typically present with a lower resting HR (RHR) [1, 4, 8]. In response to stress, both physical and psychological, the ANS initiates withdrawal of the parasympathetic nervous system and stimulation of the sympathetic nervous systems resulting in less variance between R-R intervals and a lower RMSSD [4]. As a positive response to the stresses imposed by training, the athlete will undergo adaptations related to an increased parasympathetic response that includes lower RHR and an increase in resting HRV [38, 40]. While ANS levels fluctuate from day to day, college student athletes are influenced by additional factors such as the type, intensity and length of the previous day's training and the academic pressures, such as from exams, which could result in a decrease in HRV and higher in RHR, reflective of increased sympathetic activity above the level of what would be considered a typical fluctuation [4, 24, 25, 28, 39, 77]. However, there is no clear consensus as to what is a relatively normal fluctuation for the college student athlete and what could indicate a lack of recovery from training or increases in non-training stressors [1, 8].

Methodologies for evaluating daily HRV change have used 0.5 Standard Deviation (SD) of the RMSSD or 0.5 of the individual baseline coefficient variation of the log of the RMSSD (LNRMSSD) and confidence limits (CL) of 90% in order to determine the smallest worthwhile change (SWC), the smallest change that is not due to error or normal daily fluctuations [8, 65, 66, 69, 78]. This can be interpreted that any negative change greater than 0.5 SD is indicative of increased sympathetic activity while any positive change over 0.5 SD indicates a parasympathetic adaptation and a readiness to increase activity [69]. These methods are presented in multiple studies; however the efficacy of the SWC determined by these methods has not been explored [5, 8, 69, 79, 80]. It is also important to consider the athlete's fitness level as well as the type, duration and intensity of training when examining the a level of change as recovery is unique to each individual [75]. For example, anaerobically trained athletes typically have a longer recovery time from high training loads, and for these athletes the 0.5 SD methods may be too conservative as the athletes may present with increased sympathetic activity for 48 to 72 hours post-exercise before returning to baseline [80].

In addition to the 0.5 SD driven method, several different SWC models exist as the SWC is commonly used in clinical practice to define evidence-based change [81, 82]. The SWC should account for measurement error as well as normal daily fluctuations, where a change greater than the SWC can be considered a "true" change, yet also be sensitive enough to determine a change that is clinically relevant [78, 81, 83]. To our knowledge three SWC models used in evidence-based research are identified as applicable methods to HRV data. These three statistical measures, the reliable change index (RCI), the responsiveness statistic (RS) and the standardized response mean (SRM) are deemed suitable since the measures are not based on statistical significance, are independent of sample size and are expressed as a per subject variation around a mean value [81]. The RCI, calculated as a ratio of the change to the standard error of the measurement difference, establishes confidence intervals that can be adjusted to show more conservative measures of change or as a sliding scale based on the amount of recovery from the previous day's training [81-83]. The RS, considered to be a more conservative measure, divides the change by the SD of a stable group, which takes into account normal fluctuations in HRV but does not account for individual differences. The SRM, based on the variability of individual change, is a ratio of the individual change to the SD of that change. [81] Unlike the other measures, this examines the change based on fluctuations in SD occurring as HRV changes within the athlete by utilizing not only the mean daily change of the individual but their own SD of that change, thereby accounting for differences in physiology, fitness level, recovery and even non-training stresses [75, 81]. However, the applicability of these methods for HRV data to determine the SWC has not been explored.

Athletes who continue to train without adequate recovery could experience declines in performance, and are at risk for overtraining syndrome and injury [24, 38]. If the athlete exhibits signs of a substantial increase in sympathetic activity based on the HRV measurement, training may be altered until an appropriate increase in parasympathetic activity demonstrates signs of recovery; however there is no published research quantifying the amount of change in HRV as "signs of recovery" [54, 69]. A more comprehensive analysis of the daily HRV changes in athletes would be useful to assess the efficacy of the SWC [8, 81].

Therefore the purpose of this study was to examine the daily HRV measurements in NCAA Division I Collegiate football players to assess the applicability of different SWC models. It was hypothesized that the 0.5 SD would be not be appropriate for the daily fluctuations in HRV in athletes who primarily undergo anaerobic training and may have a prolonged recovery.

METHODS

Research Design

A repeated measures design was conducted to obtain daily training load and HRV for five weeks during the participants' off-season conditioning program. Participants used a smartphone application to record HRV measures each morning. A minimum of seven consecutive baseline data points was needed to calculate change. The strength and conditioning coach provided the length of time and participant RPE for each training session for calculation of the training load. The HRV change as calculated by the change in RMSSD from the mean of the previous seven days was plugged into three formulas, the SRM, RS and RCI, and plotted against the previous day's training load. The three measures were then compared against 0.5 SD and 90% CL to assess the efficacy of these measures in determining the SWC.

Participants

Twenty NCAA Division I football players (18-25 years of age) were recruited to participate in this study during their offseason strength and conditioning workouts. Prior to inclusion in the study, participants filled out a Health History Questionnaire and informed consent form approved by the University of Hawaii Human Studies Program. Inclusionary criteria included being medically cleared to participate and currently being involved in the team's off-season training program. Exclusionary criteria included any unresolved cardiac issues.

Instruments

Daily HRV measurements were taken using the Camera Heart Rate Variability iPhone application (A.S.M.A., Eindhoven, The Netherlands) and emailed to the researcher weekly. Kubios Heart Rate Variability Software Version 2.0 (University of Kuopio, Kuopio, Finland) was used to assess time and frequency domain analysis. The Borg Ratings of Perceived Exertion scale was used along with a daily recording of the approximate length of training time to calculate training load.

Procedures

HRV Analysis

Heart rate variability data were collected daily via photo plethysmography (PPG) each morning upon waking and before practice using a smartphone application designed to measure pulse rate variability (PRV), which is analogous to HRV [68, 72]. Participants were instructed on how to use the application according to manufacturer's recommendations and completed all collections in a supine, resting position. The arterial pulse was detected using a flash on the rear-facing camera of a smartphone interfaced with an application designed to obtain signals based on blood light absorption. Participants gently placed their left index finger over the phone's camera for five minutes while signals were obtained. The smartphone application stored the data in a spreadsheet, which was then emailed directly from the phone to the strength and conditioning coach and forwarded to the researcher on a weekly basis.

The RR intervals were filtered with any ectopic beats removed prior to being imported into Kubios Heart Rate Variability Software where low-level artifact correction was applied and the sample length set to one minute and adjusted to find a stable pattern. Trend components were removed using a Smooth n Priors method. Window width for fast Fourier transformation was set at 256 seconds with the window overlap set at 50%. Interpolation of the inter-beat intervals (RR series) was set at 4 Hz. Frequency bands for HRV analysis were set as follows: very low frequency (VLF=0-0.04 Hz), low frequency (LF=0.04-0.15 Hz), and high frequency (HF=0.15-0.4 Hz). The time domain parameters (RR series) address the magnitude of variability and provide information about the vagal (parasympathetic) modulation of the heart. The frequency domain parameters provide information about parasympathetic modulation (HF), sympathovagal balance (LF), and sympathetic modulation (LF/HF). Only the time domain measure of RMSSD was used for analysis. [1]

Daily Training Load

Practice duration and intensity, as represented by self-reported RPE, was collected daily for determination of training load [76]. Participants were involved in organized conditioning activities under the direction of the strength and conditioning coach who recorded length of time of each workout as well as the intensity of that activity as reported by each participant. This information was shared with the researcher at the end of the five week training period.

Calculations of RCI and RS

The RCI and RS required data from a stable group, which was not found in the literature; therefore the calculations for the RCI and the RS relied on repeated measures data taken from another unpublished study in our lab and from participants who did not provide enough consecutive data points to be used in this study. The PRV data were collected via the same resting procedures using the Camera HRV iPhone application and analyzed using the Kubios measures outlined above with the most stable one minute period from two separate data collection sessions being used for analysis. Data were analyzed using SPSS version 24 (IBM Inc., Chicago IL) with a significance level set at p<0.05. A paired t-test was used to compare the RMSSD of resting data from two sessions taken a minimum of one week apart to calculate the SD of change. The SD of change from this stable group (n=25), 40.14, was used as the denominator in the RS for all data points. The standard error of the measurement (SEM) was calculated from the SD and the ICC of .665 then the square root of two times the SEM^2, 32.85, was used as the denominator in the RCI formula. The formulas are outlined in table 4.1.

Table 4.1: Formulas for calculating the measures of change
Formulas for the reliable change index (RCI), responsiveness statistic (RS) and standardized response mean (SRM). The numerator represents the current day's RMSSD minus the mean of the RMSSD over the previous seven days. The denominator changes for each statistic with the RCI and RS relying on data from a stable group while the SRM relies on the standard deviation of change over the previous seven days and will be different for each participant and for each data point.

	Formula
RCI	$\frac{x_1 - x_0}{\sqrt{2(\mathrm{SEM})^2}}$
RS	$\frac{x_1 - x_0}{\sqrt{\frac{\Sigma(d_{\mathrm{i\ stable}} - \bar{d}_{\mathrm{stable}})^2}{n-1}}}$
SRM	$\frac{x_1 - x_0}{\sqrt{\frac{\Sigma(d_{\mathrm{i}} - \bar{d})^2}{n-1}}}$

Statistical Analysis

The mean of the RMSSD for previous seven days was subtracted from the current day to evaluate change [70]. This change in the RMSSD was then plugged into three different statistics, the RCI, SRM, and RS to assess daily changes in HRV (see table 4.1). The RCI divides the change in RMSSD by the SEM from a stable group of participants using the same data collection procedures. The RS divides the change in RMSSD by the SD of change of a stable group using the same data collection procedures. The SRM divides the change in RMSSD by the SD of change for that individual, which was calculate based on the previous seven days of data. [81] All of the calculations result in a Z-score where 0.5 represents half of a SD and 1.645 would represent a 90% confidence interval.

RESULTS

Tables 4.2-4.8 show the results for the six participants (two defensive backs, one linebacker, one defensive lineman and two quarterbacks) who completed a minimum of eight consecutive days of data collection, missing no more than one in the previous seven, necessary to determine daily RMSSD change from the mean of the previous seven days. The days indicated on the table begin with day eight. One participant (DB2) has two separate data collection periods as he missed consecutive days at the end of week 3 and resumed collection for weeks 4 and 5. Because of the missing data points the days are not continuous and therefore to avoid confusion the graphs were not combined.

From the six participants, a total of 57 data points were included in the analysis based on the criteria. Because each of the statistical measures converted the change into a Z-score, comparisons can be made between the scores of the SRM, RS and RCI to see how each measured the individual change. If the 0.5 SD were used as a cut-off for recovery any change in RMSSD that fell below -0.5 SD as indicated by the three statistical measures would indicate a lack of readiness for the next workout. Of the 27 negative change scores, 18 showed a drop of greater than 0.5 SD with the SRM and the RS while 20 showed a drop of greater than 0.5 SD with the RCI. Of the 30 positive change scores, 21 showed a greater than 0.5 SD of improvement with the SRM, 16 with the RS and 19 with the RCI. When the 90% CI was used, there were four scores with the SRM, four scores with the RS and six scores with the RCI that fell below -1.645. Of the positive change scores there were nine SRM scores, four RS scores and eight RCI scores that fell above 1.645.

Each data collection period has three figures graphing the SRM, RS or RCI against the previous day's training load (figures 4.1 through 4.7). If the previous day was a recovery day there is no accompanying bar as the training load would be zero. Participants had training on Monday, Tuesday, Thursday and Friday with Wednesday, Saturday and Sunday as designated days off from formal training. The participants underwent a standard training protocol developed by the strength and conditioning coach with adjustments made to the weight training based on the abilities of each participant. Any additional outside training or recreational activities were not restricted and were not included in the training load.

Figure 4.1a: Plotting the standardized response mean (SRM) on the left y-axis against the previous day's training load (PDTL), the product of the minutes trained times the Rating of Perceived Exertion (RPE) on the right y-axis for subject DB1 for 6 days. On days where there was no formal practice, the PDTL is zero.

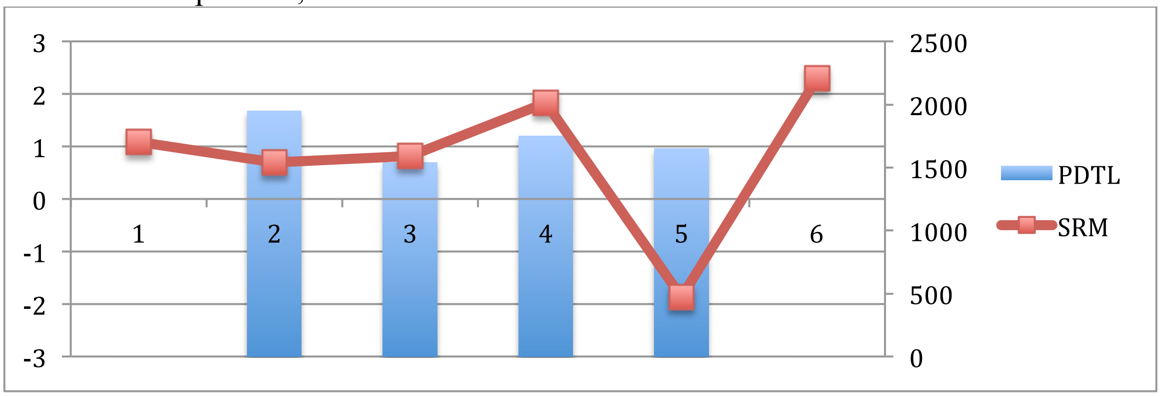


Figure 4.1b: Plotting the responsiveness statistic (RS) on the left y-axis against the previous day's training load (PDTL), the product of the minutes trained times the Rating of Perceived Exertion (RPE) on the right y-axis for subject DB1 for 6 days. On days where there was no formal practice, the PDTL is zero.

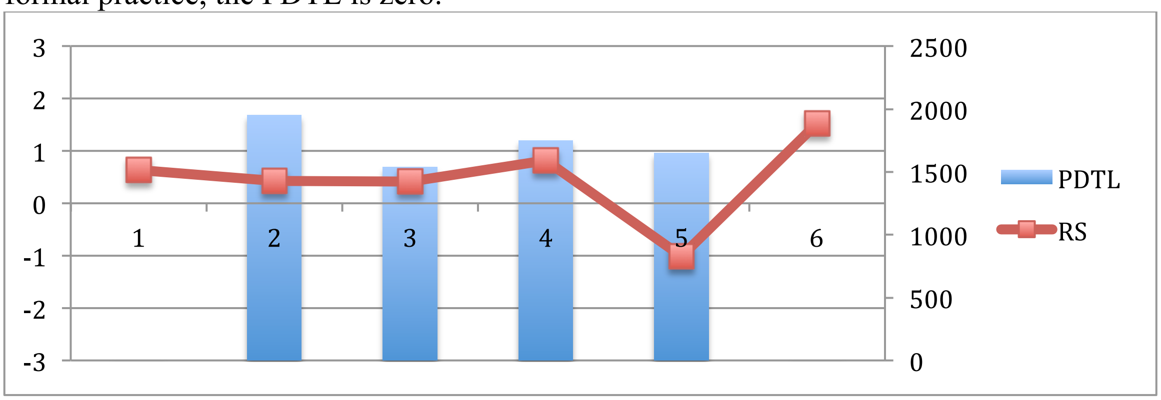


Figure 4.1c: Plotting the recovery change index (RCI) on the left y-axis against the previous day's training load (PDTL), the product of the minutes trained times the Rating of Perceived Exertion (RPE) on the right y-axis for subject DB1 for 6 days. On days where there was no formal practice, the PDTL is zero.

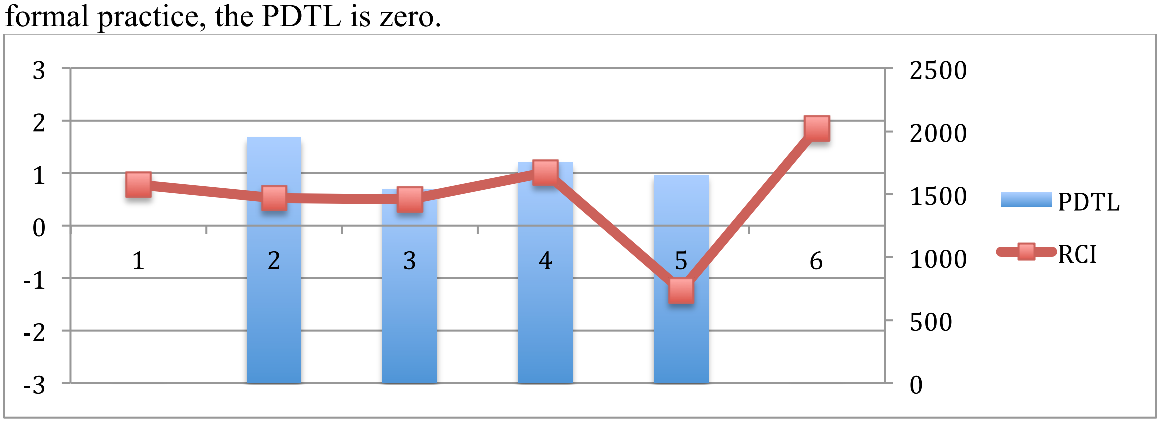


Figure 4.2a: Plotting the standardized response mean (SRM) on the left y-axis against the previous day's training load (PDTL), the product of the minutes trained times the Rating of Perceived Exertion (RPE) on the right y-axis for subject DB2 for 12 days. On days where there was no formal practice, the PDTL is zero.

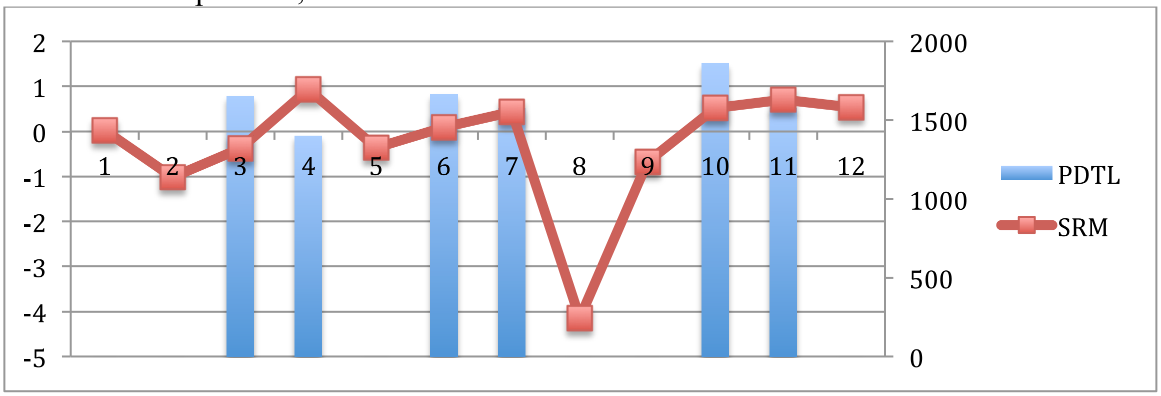


Figure 4.2b: Plotting the responsiveness statistic (RS) on the left y-axis against the previous day's training load (PDTL), the product of the minutes trained times the Rating of Perceived Exertion (RPE) on the right y-axis for subject DB2 for 12 days. On days where there was no formal practice, the PDTL is zero.

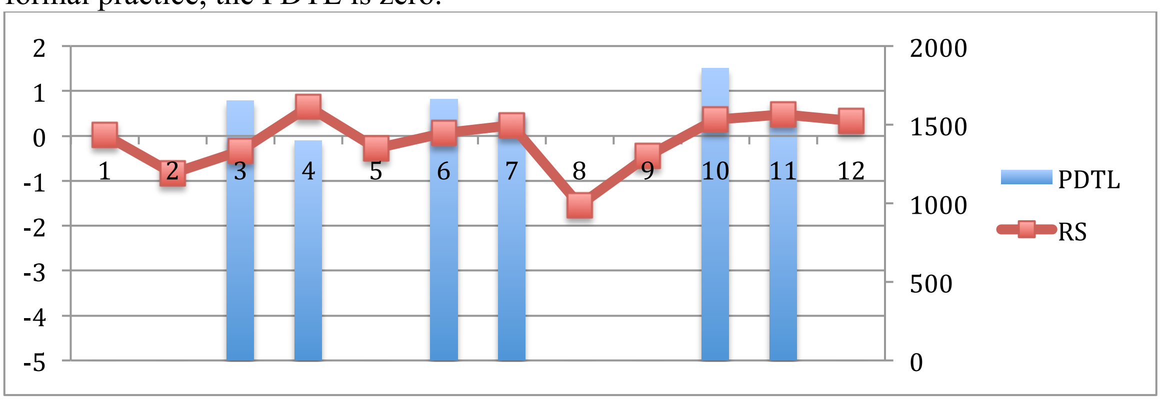


Figure 4.2c: Plotting the recovery change index (RCI) on the left y-axis against the previous day's training load (PDTL), the product of the minutes trained times the Rating of Perceived Exertion (RPE) on the right y-axis for subject DB2 for 12 days. On days where there was no formal practice, the PDTL is zero.

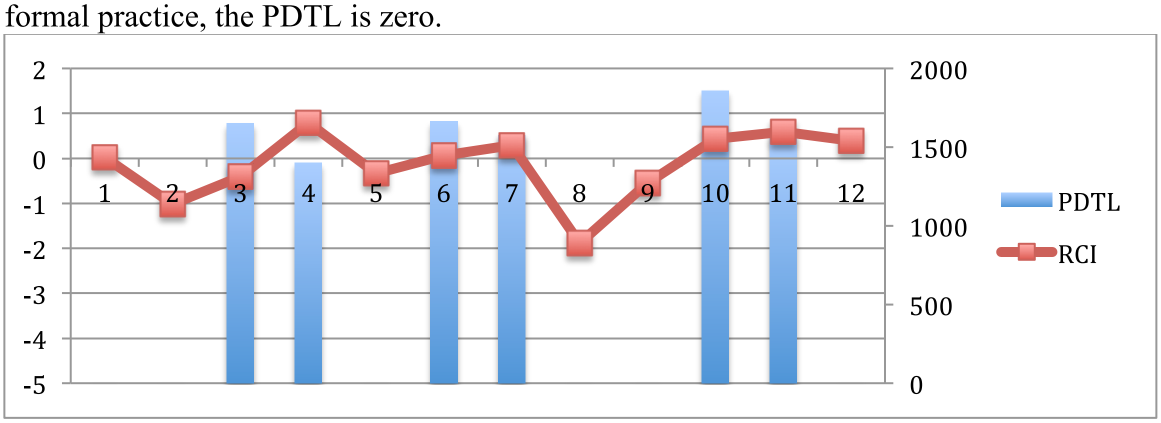


Figure 4.3a: Plotting the standardized response mean (SRM) on the left y-axis against the previous day's training load (PDTL), the product of the minutes trained times the Rating of Perceived Exertion (RPE) on the right y-axis for subject DB2 for 8 days. On days where there was no formal practice, the PDTL is zero.

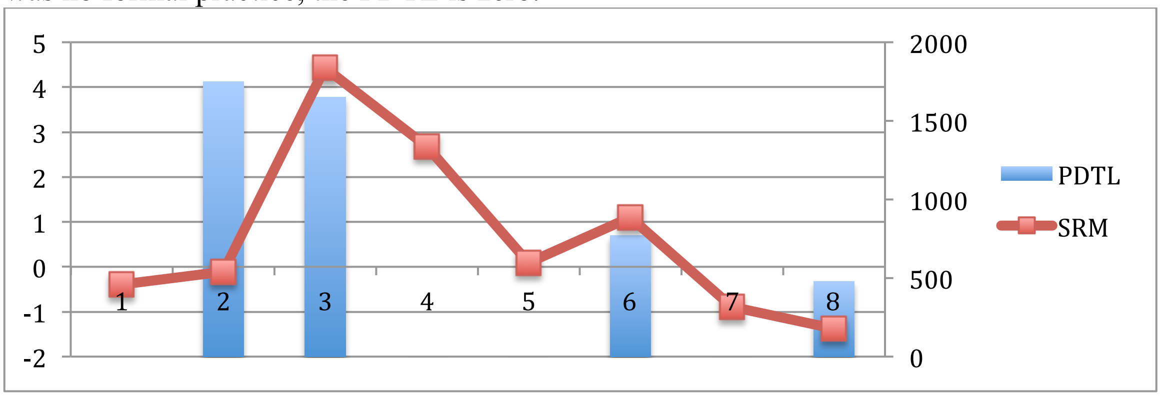


Figure 4.3b: Plotting the responsiveness statistic (RS) on the left y-axis against the previous day's training load (PDTL), the product of the minutes trained times the Rating of Perceived Exertion (RPE) on the right y-axis for subject DB2 for 8 days. On days where there was no formal practice, the PDTL is zero.

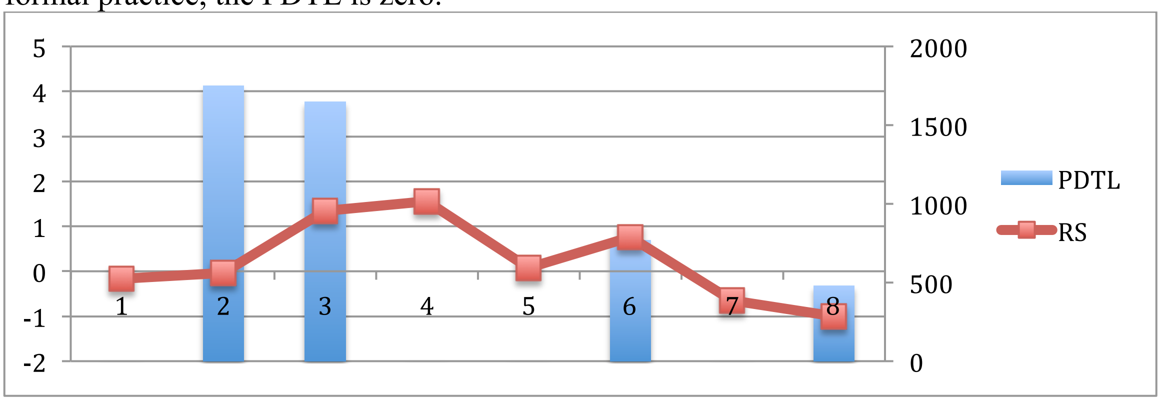


Figure 4.3c: Plotting the recovery change index (RCI) on the left y-axis against the previous day's training load (PDTL), the product of the minutes trained times the Rating of Perceived Exertion (RPE) on the right y-axis for subject DB2 for 8 days. On days where there was no formal practice, the PDTL is zero.

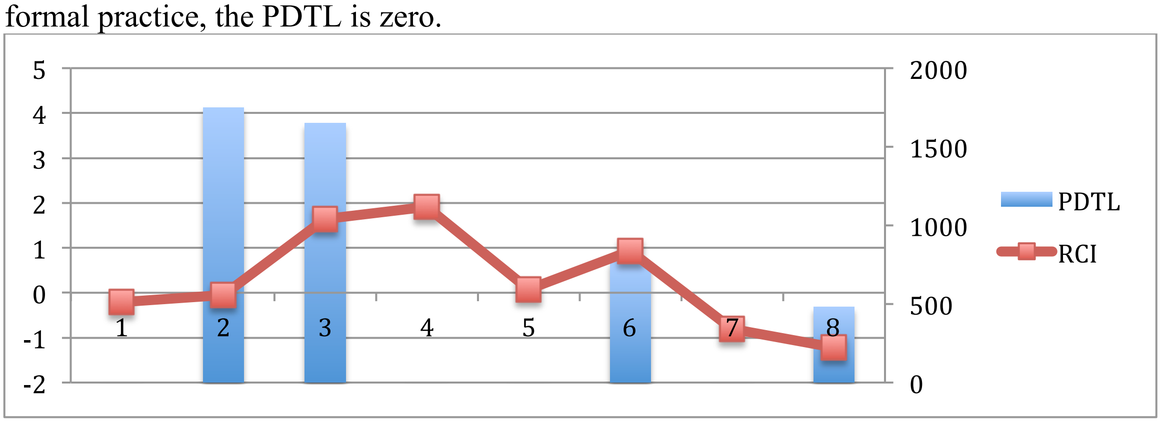


Figure 4.4a: Plotting the standardized response mean (SRM) on the left y-axis against the previous day's training load (PDTL), the product of the minutes trained times the Rating of Perceived Exertion (RPE) on the right y-axis for subject DL1 for 5 days. On days where there was no formal practice, the PDTL is zero.

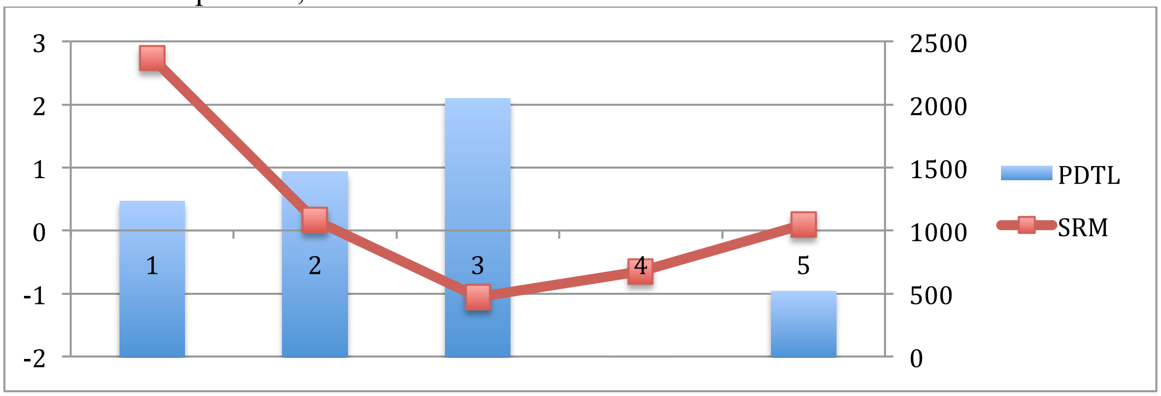


Figure 4.4b: Plotting the responsiveness statistic (RS) on the left y-axis against the previous day's training load (PDTL), the product of the minutes trained times the Rating of Perceived Exertion (RPE) on the right y-axis for subject DL1 for 5 days. On days where there was no formal practice, the PDTL is zero.

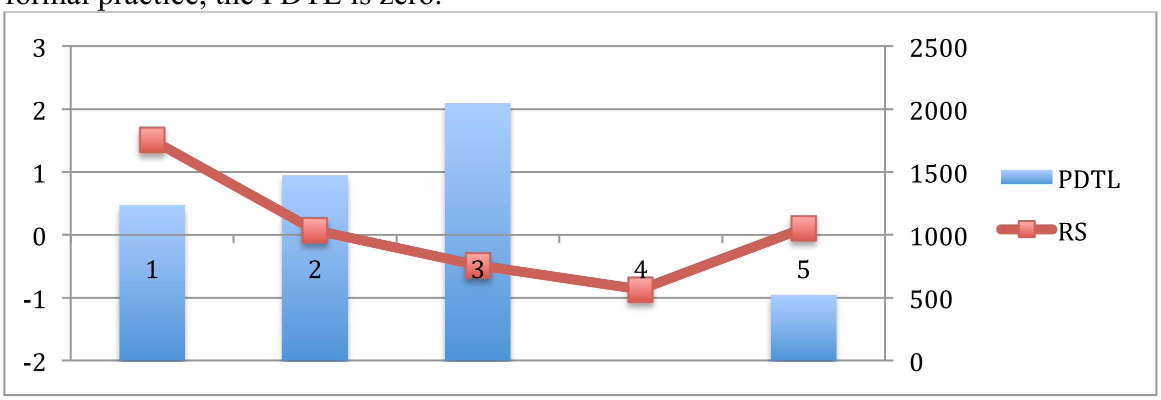


Figure 4.4c: Plotting the recovery change index (RCI) on the left y-axis against the previous day's training load (PDTL), the product of the minutes trained times the Rating of Perceived Exertion (RPE) on the right y-axis for subject DL1 for 5 days. On days where there was no formal practice, the PDTL is zero.

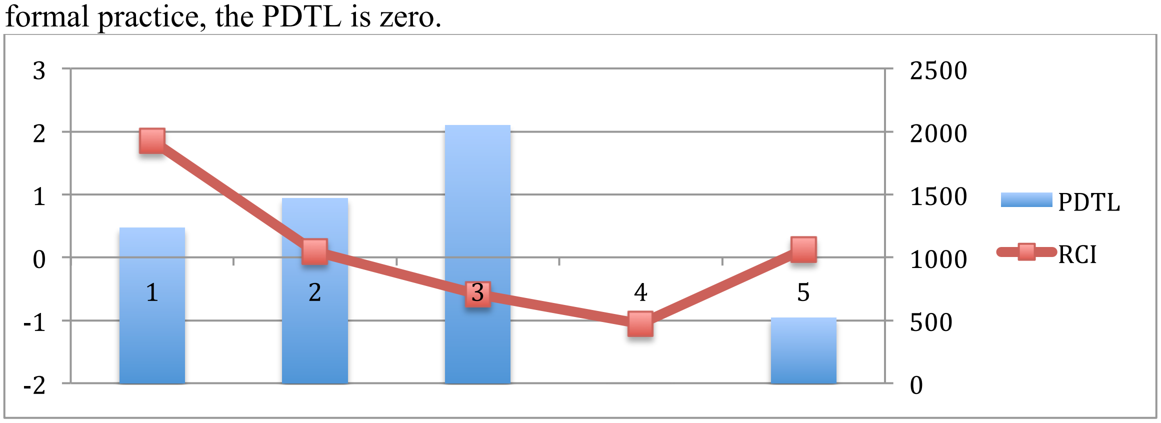


Figure 4.5a: Plotting the standardized response mean (SRM) on the left y-axis against the previous day's training load (PDTL), the product of the minutes trained times the Rating of Perceived Exertion (RPE) on the right y-axis for subject LB1 for 18 days. On days where there was no formal practice, the PDTL is zero.

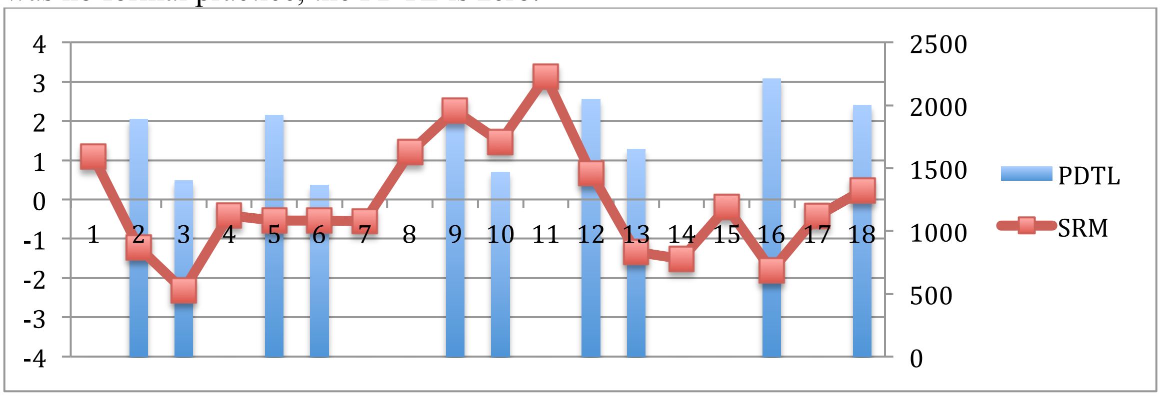


Figure 4.5b: Plotting the responsiveness statistic (RS) on the left y-axis against the previous day's training load (PDTL), the product of the minutes trained times the Rating of Perceived Exertion (RPE) on the right y-axis for subject LB1 for 18 days. On days where there was no formal practice, the PDTL is zero.

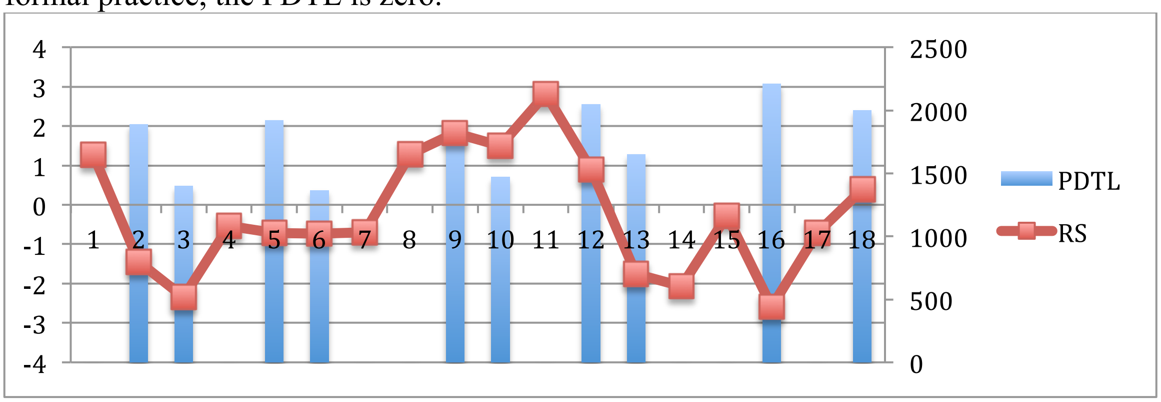


Figure 4.5c: Plotting the recovery change index (RCI) on the left y-axis against the previous day's training load (PDTL), the product of the minutes trained times the Rating of Perceived Exertion (RPE) on the right y-axis for subject LB1 for 18 days. On days where there was no formal practice, the PDTL is zero.

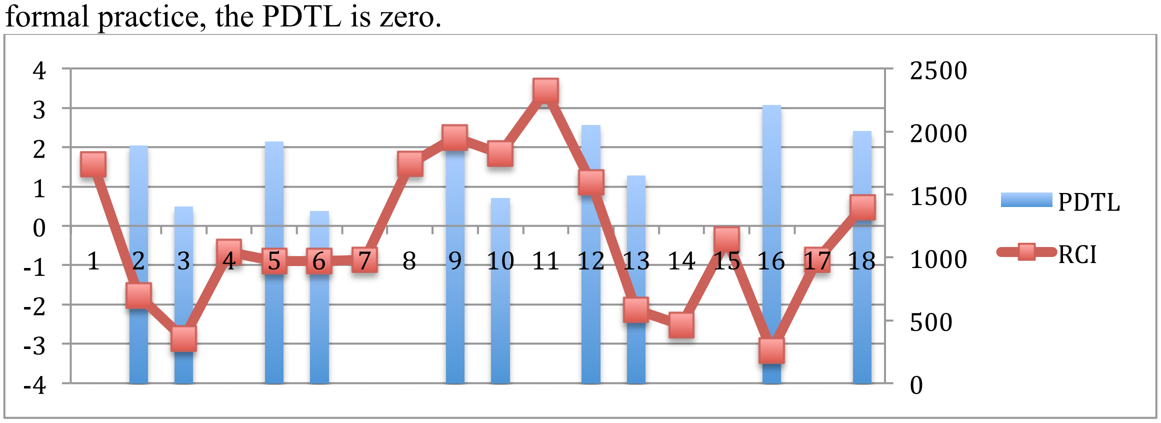


Figure 4.6a: Plotting the standardized response mean (SRM) on the left y-axis against the previous day's training load (PDTL), the product of the minutes trained times the Rating of Perceived Exertion (RPE) on the right y-axis for subject QB1 for 5 days. On days where there was no formal practice, the PDTL is zero.

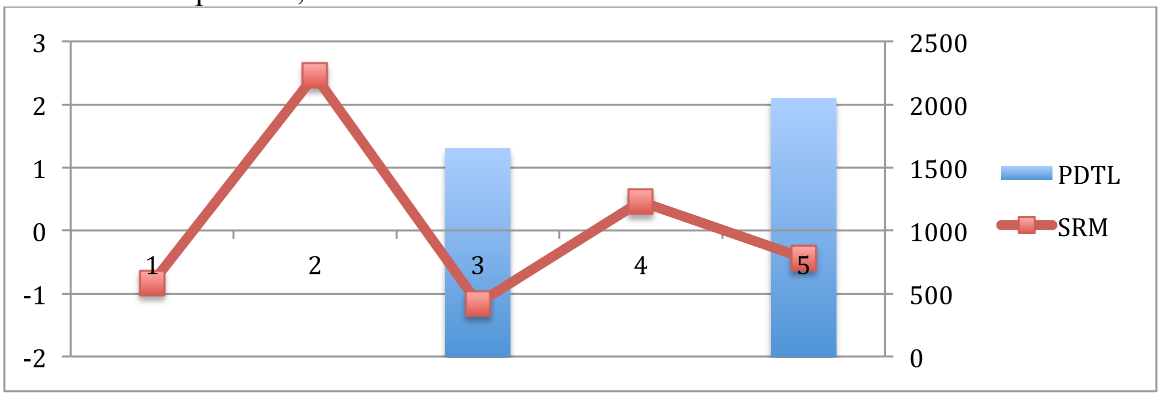


Figure 4.6b: Plotting the responsiveness statistic (RS) on the left y-axis against the previous day's training load (PDTL), the product of the minutes trained times the Rating of Perceived Exertion (RPE) on the right y-axis for subject QB1 for 5 days. On days where there was no formal practice, the PDTL is zero.

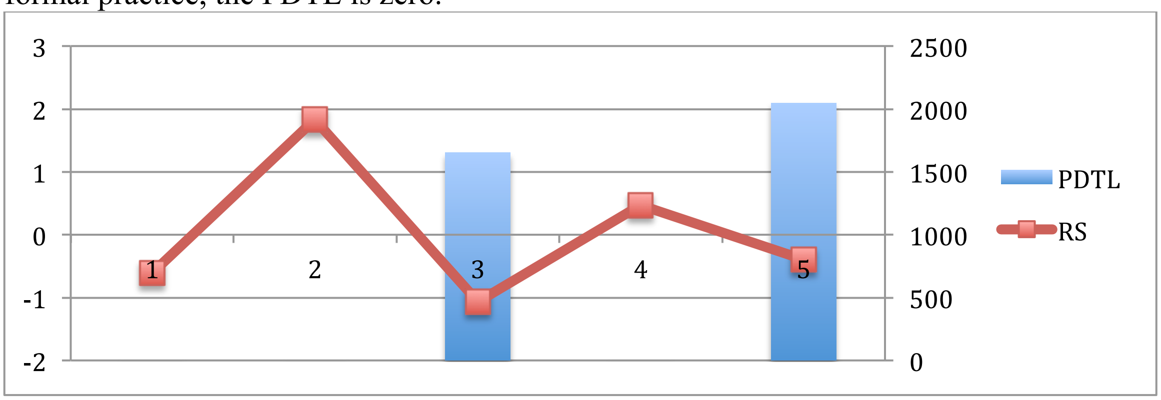


Figure 4.6c: Plotting the recovery change index (RCI) on the left y-axis against the previous day's training load (PDTL), the product of the minutes trained times the Rating of Perceived Exertion (RPE) on the left y-axis for subject QB1 for 5 days. On days where there was no formal practice, the PDTL is zero.

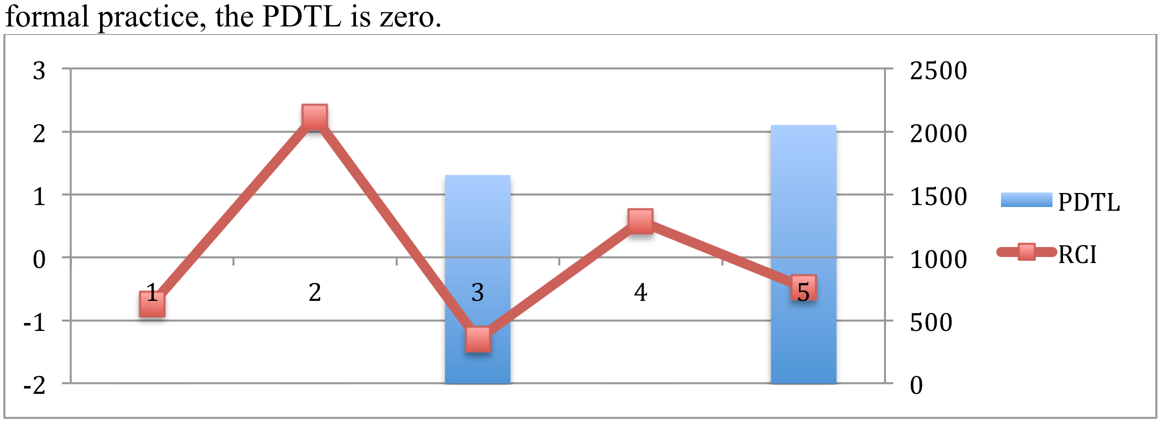


Figure 4.7a: Plotting the standardized response mean (SRM) on the left y-axis against the previous day's training load (PDTL), the product of the minutes trained times the Rating of Perceived Exertion (RPE) on the right y-axis for subject QB2 for 3 days. On days where there was no formal practice, the PDTL is zero.

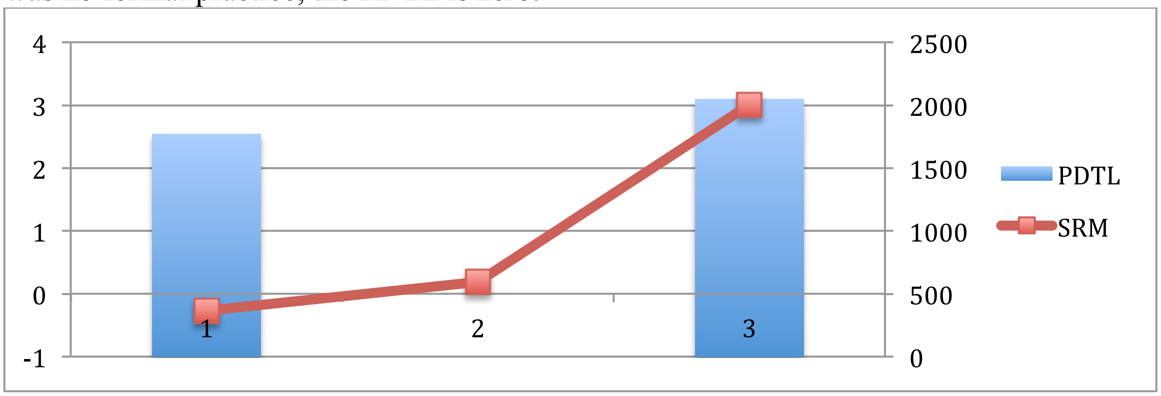


Figure 4.7b: Plotting the responsiveness statistic (RS) on the left y-axis against the previous day's training load (PDTL), the product of the minutes trained times the Rating of Perceived Exertion (RPE) on the right y-axis for subject QB2 for 3 days. On days where there was no formal practice, the PDTL is zero.

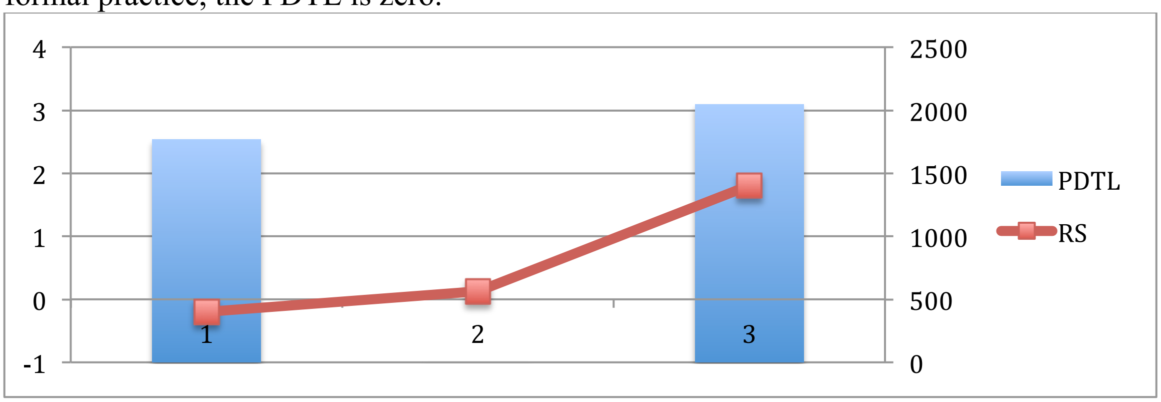
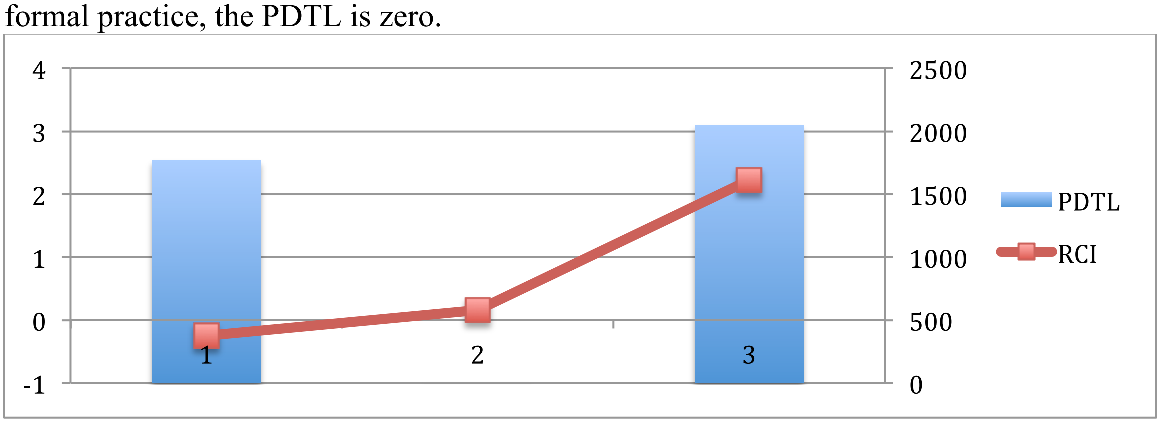


Figure 4.7c: Plotting the recovery change index (RCI) on the left y-axis against the previous day's training load (PDTL), the product of the minutes trained times the Rating of Perceived Exertion (RPE) on the right y-axis for subject QB2 for 3 days. On days where there was no formal practice, the PDTL is zero.



DISCUSSION

Daily HRV measurements can be used to track overall change in the sympathovagal balance as training will produce fluctuations in HRV from day to day based on the demands of the session, type of training and the level of fitness of the individual; however there is no clear consensus as to the what level of change is appropriate and what could reflect a lack of recovery [8, 49]. The three statistical analyses proposed here are used in other disciplines to bridge the gap between research and clinical practice and are being evaluated for their potential with HRV. The RS and RCI are all based on normative values, typically from large data sets, to determine the amount of appropriate change [81]. While this may be appropriate in other areas of evidence-based practice where measures can be used for comparison against large groups, gender, age, type of exercise, and fitness level can all influence HRV recovery time making the use of "normative" data from different sports or genders questionable [80, 84, 85]. In addition, HRV comparisons can only accurately be made if there is similar methodologies of data collection, including the length of recording time, calculation of frequency domain variables and data collection instrument [1]. To allow for these differences, the SD of change and the SEM calculations for the RS and RCI used one-minute of stable HRV data collected via the same smartphone application used in the daily data collections and used only NCAA Division I athletes, however males and females participating in endurance and non-endurance sports were included which may have altered the SD and SEM measures. Therefore using the SD of the mean change of that individual as in the SRM would allow for an equation that would be more applicable than the RS or the RCI unless normative values and normative change measures can be established in collegiate male football players.

Based on the comparison of the SWC models, the traditional 0.5SD model seemed too conservative for the amount of fluctuation experience by NCAA Division I football players during off-season strength and conditioning sessions. Of the 57 data points outlined in tables 2-8, only 18 from the SRM, 23 from the RS and 18 from the RCI fell between -0.5 SD and 0.5 SD which could be interpreted as the majority of the workouts being either too difficult, producing a greater than -0.5 SD decrease in HRV, or too easy, producing a greater than 0.5 SD increase in HRV. The workouts being too hard or too easy is not supported by the subjective assessment of the workouts as the RPE measures taken after each session were typically from 14 to16 for the first four weeks and from 9 to 11 for the fifth week and there was no consistency in the amount of change to HRV and the previous day's training load. As most of the research related to daily HRV focuses on endurance athletes who typically undergo aerobic, steady-state training the 0.5SD level may be too sensitive for the anaerobic based strength and conditioning workouts of the football players. When 0.5 SD was used as a cutoff to decrease training in female recreational endurance runners, only one participant was unable to complete the training because her SWC was consistently below the -0.5 SD cutoff point; however the HRV measures for female recreational endurance athletes (age 34±8 years) and collegiate male football players are not comparable and therefore these differences may account for the difference in results [69]. The neuromuscular repair after muscle-damaging exercise such as strength training can demand more energy than recovery from aerobic training which could lead to prolonged sympathetic activity and therefore it is suggested to use the data two days after an intense strength training session to obtain change rather than the next day [80].

The 90% CI was less sensitive to the daily fluctuations as only ten of the SRM points, eight of the RS and fourteen of the RCI fell outside of the interval of -1.645 to 1.645 as determined by the z-score in each of the statistical measures. While multiple participants had back-to-back days with changes outside 0.5 SD, only participant LB1 had negative changes outside of the 90% CI on two consecutive days with the RS and RCI but not with the SRM. This negative change was associated with the highest recorded RPE, 17, therefore having the additional subjective information along with the HRV measures helps explain the delay in recovery. The changing SD with the SRM explains why there was no negative change outside of the 90% CI for this measure, making it more adaptive to the normal fluctuations of training. Training sessions in this study featured both strength and conditioning activities appropriate for football, which does not require an extended period in steady-state. Interval training and training above the lactate threshold, as seen in football related conditioning exercises, can lead to a delay in the return to autonomic balance as opposed to steady-state endurance training combined with strength training, which has been shown to improve parasympathetic activity [48, 85]. The lack of steady-state would require the ANS to continually balance between the sympathetic and parasympathetic systems, which may result in the delayed return of parasympathetic levels. The results of this study are similar to what was reported by Flatt, et al., where female soccer players had greater change above the 90% CI with a hard training load week compared to a low training load week [66].

Coaches are seeking an easy way to interpret the most relevant information about the subjective and objective data from the athlete in order to monitor training on a daily or a weekly basis [86]. The SRM transforms the change score into an easily interpretable z-score calculated using an excel spreadsheet. When graphed against the previous day's training load, as illustrated in the figures, athletes and coaches can track the progress and the amount of change from day to day. The HRV measures will fluctuate on a daily basis, therefore return to baseline is not expected, however the degree of change, positive or negative, and the ability to track that change over time is what is important. For example, if the intent of a particular week is produce overload it can be displayed graphically comparing the training load against HRV changes which when taken in context does not necessarily mean that the participant is at risk for overtraining however if the increased sympathetic activity occurs, adjustments to training or recovery can be made [87]. This would also allow for easier comparison between athletes during training as each person has their own z-score graphed against the training load that includes individual RPE measures and does not rely on a "normative" value table.

This research presents three statistical analyses that have the potential to be used to track changes in HRV during training although defining the SWC likely depends as much on the training context as the statistical measure being used to evaluate the level of change. While the appropriate amount of change cannot be determined from this small sample size, the 0.5SD appears to be too conservative of a measure on which to evaluate change. The 90% CI appears to be a more appropriate measure of change in collegiate male football players during off-season conditioning. In addition, it is important to consider the level of change over consecutive days when evaluating anaerobic exercise, and looking at the change at two days post-training instead of one day. These statistics may provide a methodology for which future research can be based, however more research into the efficacy of these measures with a variety of athletes and sports is needed.

Table 4.2: Daily HRV changes for Subject DB1 for 6 days

Subject	Mean HR	RMSSD	7-day mean RMSSD	Daily change from 7-day	SRM	RS	RCI	Previous Day's Training Load
DB1.D1	53.61	101.5	76.96	25.67	1.09	0.64	0.78	0
DB1.D2	68.17	94.3	74.01	17.34	0.70	0.43	0.53	1950
DB1.D3	63.71	90.6	79.70	16.59	0.82	0.41	0.50	1540
DB1.D4	66.95	112.8	85.40	33.10	1.83	0.82	1.01	1750
DB1.D5	77.68	45	81.07	-40.40	-1.87	-1.01	-1.23	1650
DB1.D6	58.18	141.9	94.67	60.83	2.30	1.52	1.85	0

Table 4.3: Daily HRV changes for Subject DB2 for 12 consecutive days

Subject	Mean HR	RMSSD	7-day mean RMSSD	Daily change from 7-day	SRM	RS	RCI	Previous Day's Training Load
DB2.D1	50.37	108.3	107.83	0.83	0.03	0.02	0.03	0
DB2.D2	62	74.6	104.33	-33.23	-1.01	-0.83	-1.01	0
DB2.D3	51.49	91	95.59	-13.33	-0.38	-0.33	-0.41	1652
DB2.D4	63.84	121.7	100.30	26.11	0.93	0.65	0.79	1400
DB2.D5	51.69	89.6	92.86	-10.70	-0.36	-0.27	-0.33	0
DB2.D6	53.4	95.2	90.64	2.34	0.10	0.06	0.07	1664
DB2.D7	55.24	100.1	97.21	9.46	0.43	0.24	0.29	1575
DB2.D8	73.53	35.2	86.77	-62.01	-4.15	-1.54	-1.89	0
DB2.D9	56.35	68.6	85.91	-18.17	-0.68	-0.45	-0.55	0
DB2.D10	52.96	100.2	87.23	14.29	0.52	0.36	0.43	1860
DB2.D11	49.17	106.6	85.07	19.37	0.70	0.48	0.59	1575
DB2.D12	49.26	98.3	86.31	13.23	0.53	0.33	0.40	0

Table 4.4: Daily change for subject DB2 for 8 consecutive days

Subject	Mean HR	RMSSD	7-day mean RMSSD	Daily change from 7-day	SRM	RS	RCI	Previous Day's Training Load
DB2.D20	60.43	79.9	83.79	-6.79	-0.40	-0.17	-0.21	0
DB2.D21	65.72	82.1	80.29	-1.69	-0.11	-0.04	-0.05	1750
DB2.D22	57.09	134.2	85.41	53.91	4.43	1.34	1.64	1650
DB2.D23	59.73	148.1	97.59	62.69	2.68	1.56	1.91	0
DB2.D24	58.86	100.2	102.20	2.61	0.09	0.07	0.08	0
DB2.D25	51.38	132.9	108.24	30.70	1.10	0.76	0.93	770
DB2.D26	72.05	82.1	108.50	-26.14	-0.89	-0.65	-0.80	0
DB2.D27	51.48	68.3	106.84	-40.20	-1.38	-1.00	-1.22	480

Table 4.5: Daily change for subject DL1 for 5 consecutive days

Subject	Mean HR	RMSSD	7-day mean RMSSD	Daily change from 7-day	SRM	RS	RCI	Previous Day's Training Load
DL1.D1	60.79	158.9	102.83	60.80	2.74	1.51	1.85	1235
DL1.D2	69.29	94.6	91.73	2.89	0.16	0.07	0.09	1470
DL1.D3	71.97	72.2	89.60	-19.53	-1.06	-0.49	-0.59	2048
DL1.D4	62.42	71	110.96	-34.89	-0.65	-0.87	-1.06	0
DL1.D5	62.59	115	116.89	4.04	0.09	0.10	0.12	520

Table 4.6: Daily change for subject LB1 for 18 consecutive days

Subject	Mean HR	RMSSD	7-day mean RMSSD	Daily change from 7-day	SRM	RS	RCI	Previous Day's Training Load
LB1.D1	46.66	203.4	153.21	51.16	1.09	1.27	1.56	0
LB1.D2	54.13	94.9	156.97	-58.31	-1.22	-1.45	-1.78	1888
LB1.D3	55.01	62.9	149.21	-94.07	-2.31	-2.34	-2.86	1400
LB1.D4	47.28	127.4	147.39	-21.81	-0.41	-0.54	-0.66	0
LB1.D5	54.03	118.3	140.03	-29.09	-0.54	-0.72	-0.89	1920
LB1.D6	49.46	110.9	130.49	-29.13	-0.54	-0.73	-0.89	1365
LB1.D7	46.24	102.3	117.16	-28.19	-0.55	-0.70	-0.86	0
LB1.D8	42.29	169	112.24	51.84	1.20	1.29	1.58	0
LB1.D9	43.55	185.7	125.21	73.46	2.26	1.83	2.24	1860
LB1.D10	44.68	185.6	142.74	60.39	1.46	1.50	1.84	1470
LB1.D11	44.29	255.7	161.07	112.96	3.12	2.81	3.44	0
LB1.D12	46.7	197.3	172.36	36.23	0.66	0.90	1.10	2048
LB1.D13	50.95	102.3	171.13	-70.06	-1.33	-1.75	-2.13	1650
LB1.D14	48.23	88.3	169.13	-82.83	-1.52	-2.06	-2.52	0
LB1.D15	45.96	157.9	167.54	-11.23	-0.20	-0.28	-0.34	0
LB1.D16	60	63.5	150.09	-104.04	-1.80	-2.59	-3.17	2210
LB1.D17	52.62	121.5	140.93	-28.59	-0.42	-0.71	-0.87	0
LB1.D18	49.52	156.5	126.76	15.57	0.23	0.39	0.47	2000

Table 4.7: Daily change for subject QB1 for 5 days

Subject	Mean HR	RMSSD	7-day mean RMSSD	Daily change from 7-day	SRM	RS	RCI	Previous Day's Training Load
QB1.D1	56.31	73.6	92.33	-24.30	-0.83	-0.61	-0.74	0
QB1.D2	52.03	165.7	107.26	73.37	2.46	1.83	2.23	0
QB1.D3	57.3	64.5	102.56	-42.76	-1.16	-1.07	-1.30	1652
QB1.D4	49.52	121.3	98.31	18.74	0.46	0.47	0.57	0
QB1.D5	50.25	82.5	99.77	-15.81	-0.44	-0.39	-0.48	2048

Table 4.8: Daily change for subject QB2 for 3 days

Subject	Mean HR	RMSSD	7-day mean RMSSD	Daily change from 7-day	SRM	RS	RCI	Previous Day's Training Load
QB2.D1	52.04	82.8	94.87	-8.09	-0.27	-0.20	-0.25	1770
QB2.D2	50.14	100	91.89	5.13	0.19	0.13	0.16	0
QB2.D3	47.76	164.7	96.24	72.81	3.01	1.81	2.22	2048

Tables 4.2 to 4.8: All data are presented as a one-minute average taken from the most stable sixty second period of a five minute morning data collection. Presented variables include the mean heart rate (HR), the root mean square of the standard deviation of the RR intervals (RMSSD), the mean RMSSD of the previous seven days, the daily change presented as the previous seven day mean subtracted from the current day, the standardized response mean (SRM), the response statistic (RS), the recovery change index (RCI) and the previous day's training load, the product of the minutes trained times the rating of perceived exertion (RPE). On days of no formal practice the previous day's training load was calculated as zero.

Review of Literature

Overtraining and Underrecovery

Effective training must provide a combine training loads that will balance improvement in performance with recovery [24, 30, 38, 55]. Without appropriate recovery, overtraining will occur [30, 38, 55]. The consensus is that overtraining begins with a state of overreaching, both function and nonfunctional, before an overtraining syndrome (OTS) were to occur [24, 38, 40]. There is no specific diagnostic criteria for overtraining, however the European College of Sport Science and the American College of Sports Medicine have recognized various physiological, biochemical and psychological symptoms that may be of use by coaches, athletes and athletic trainers in the diagnosis of overtraining [24, 25, 28]. The development of appropriate diagnostic criteria would need to involve both quantitative and qualitative symptoms [30, 45]. Current research agrees that daily monitoring of training load is the best way to determine the effects of training on physiological and psychological changes, but has not yet determined which stressors are a normal part of adaptation and which will lead to OTS [24, 25, 61].

The goal of a training program is to improve function and optimize performance through repetitive exercise. Repetition improves motor skills and provides physiological adaptations to the structural and metabolic functions of the body. Training involves increasing intensity, duration and frequency but must also allow for recovery from a previous excessive or trainable load. Periodization allows for an athlete to peak at a particular event with a taper period set prior to an event to allow for recovery and enhance performance. Overreaching occurs as an accumulation of training and non-training stresses result in a decrease in performance, which should reverse in one to two weeks with adequate recovery, leading to a supercompensation state. Unlike overreaching, overtraining is when these training stresses are not balanced with adequate recovery and leads to a decrease in performance and an altered mood state. Strategies for avoiding overtraining involve a progressive increase in training with a particular event or events delegated for peak performance. Training can be monitored by physiological variables and should have for adequate recovery time periods built in. [30]

Training leads to physiological changes to the heart, typically evaluated as the left ventricular adaptations, in order to adapt to the stresses put on it. In a review of meta-analyses on the chronic left ventricle changes found in the athlete heart, there were clear differences among subgroups of dynamic athletes. Male distance runners, compared to sedentary controls, had a lower HR, larger left ventricular internal diameter and thicker posterior and septal walls. Ultra endurance athletes had a more pronounced left ventricular mass than amateur distance runners and the increase in thickness to the ventricular walls was more pronounced than expected for a purely eccentric left ventricular hypertrophy. Swimmers also had a significant increase in left ventricle diameter and mass compared to controls, however the small differences in wall thickness were not significant, indicating eccentric left ventricle hypertrophy. Competitive cycling is associated with an increase in internal diameter and a disproportionate increase in wall thickening compared to sedentary controls and recreational cyclists. This change can be related to both the static positioning of the upper body during cycling and to the larger training quantity of these athletes. Sprinting, a dynamic anaerobic exercise resulted in male and female athletes with cardiac changes associated with eccentric left ventricular hypertrophy. Athletes competing in ball sports such as basketball, softball and field hockey had results compatible with eccentric left ventricular hypertrophy. Those athletes where strength training is a large component did have absolute and relative wall thickness that was higher than controls, but also had a higher left ventricle internal diameter. However, because most collegiate athletes engage in training that has both static and dynamic components, their relative changes may not be reflective of just one type of training. These changes not only improve performance but may also help to improve recovery. [88]

Disruption to the balance of training stress and recovery can lead to an abnormal training response. Overreaching is an accumulation of stress that results in a short-term decrease in performance, with or without related psychological and physiological symptoms. If left untreated, the long-term overtraining response may occur which would require a recovery taking weeks to months. Overtraining syndrome refers to the multifactorial etiology and emphasizes that training is not the sole causative factor of the syndrome. There is currently no relevant tool for the diagnosis of overtraining, however a variety of factors have been identified. As the inability to sustain performance is a hallmark of OTS, performance tests, which are sport specific, intense and reproducible, can be used to evaluate for OTS. In the event that these tests are not available, training journals and competition results could potentially be substituted. The psychological component of OTS can be assessed using validated questionnaires, such as the Recovery-Stress Questionnaire for Athletes (REST-Q Sport), which monitors for levels of general as well as sport specific stresses. Physiological variables, such as heart rate variability (HRV) can be utilized, however it has not provided consistent results. Combining psychological and physiological measures has the potential to be more effective. Other factors to consider in OTS include sleep and rest, nutrition, hormonal changes and immunological considerations. There is a complex set of psychological and physiological factors that must be considered in OTS and the use of a checklist has been recommended for diagnosis. [24]

The borderline between optimal performance and performance impairment from OTS is subtle. In diagnosis of OTS it is important to exclude organic diseases, infections and other factors such as nutritional concerns. Athletes and coaches would benefit from a specific and sensitive test for the diagnosis of OTS, yet one does not exist. This lack of definitive diagnostic criteria is reflected in the research by a lack of consistent findings. The position statement includes assessment of physical performance, mood state, biochemistry, hormonal data and immunological testing. Prevention, by monitoring the balance of training loads and recovery, seems to be one of the ways to overcome the lack of clear diagnostic testing. Journaling and using training logs seems to show the most promise. Athletes and coaches can keep track of subjective parameters such as soreness and mental and physical well-being as well as subjective training data, including heart rate (HR), training loads, rating of perceived exertion (RPE) and recovery time. [25]

The most common signs of OTS include pronounced fatigue and decline in performance despite continued training. Other symptoms should not be discounted such as changes in motivation and anxiousness. Changes in mood are typically noted with OTS, however it can be difficult to quantify and has not been validated against physiological measures. Depending on the type of training, the associated physical symptoms of OTS may be different. Endurance or aerobic sports include more parasympathetic alterations such as fatigue and resting HR changes while anaerobic sports include more sympathetic alterations such as increased HR and blood pressure (BP). Specific biomarkers for autonomic nervous system (ANS) changes remain to be identified. Typically an increase in resting HR and a reduction in maximal HR are associated with OTS, however this has not been consistent in the literature possibly due to differing methodologies. With a standardized methodology, the use of HRV may be a better noninvasive tool for predicting OTS as it can reflect the balance of the sympathetic and parasympathetic nervous systems. Because OTS has components of mental and emotional factors along with physical physiological symptoms, diagnosis of OTS should use components that can assess multiple factors. [28]

Numerous hypotheses have been postulated to explain the pathophysiology of OTS. The microtrauma to the muscles that may occur with intense training can stimulate a local inflammatory response triggering cytokine recruitment. Acute inflammation without appropriate recovery could lead to chronic inflammation as seen with overuse injuries, however there is little evidence to support the cytokine theory with OTS. Decreased glycogen levels can negatively effect performance as the athlete does not have enough stored energy to complete their training leading to fatigue, however just consuming enough carbohydrates is not enough to prevent OTS. Blood lactate levels, which have an inverse relationship to glycogen levels and can therefore be a potential marker of OTS however lactate levels alone cannot be used to diagnose OTS. Monitoring HR before and during activities as well as HRV levels at rest and making comparisons to baseline levels can be useful in determining OTS assuming the abnormalities in HR are not attributed to another cause. The use of questionnaires such as the RESTQ-Sport and the Profile of Mood States (POMS) could provide an indication of increased stress levels. Combining the questionnaire with physical measures may give the best indication of OTS as well as the potential methods for appropriate recovery. [39]

Typically, OTS mainly affects endurance athletes and is associated with frequent infections and depression with no identifiable medical cause following hard training and competition. These symptoms will fail to resolve despite adequate rest. Underrecovery as a result of excessively prolonged and/or intense exercise, stressful competition or other stresses leads to progressive fatigue and underperformance. The main complaint of OTS is underperformance, with the athlete often ignoring fatigue, heavy muscles and depression.

Additional physiological responses include raised resting pulse rate, excessive sweating, frequent minor infections, reduced VO_2max, reduced maximum power and increased submaximal oxygen consumption with a slow heart rate recovery (HRR). As there is no specific diagnostic test available for OTS, it is best to first rule out any other causes of pathology. Careful monitoring of athletes and their training may help to prevent the syndrome. The best treatment involves complete rest, which may be difficult for many endurance athletes to comply therefore a reduction in training or just allowing for light exercise may be the better approach. [52]

If sufficient rest is not included in a training program, optimal balance cannot be maintained between training sessions and recovery, regeneration fails to occur and as a result performance plateaus and eventually decreases. Sports with greater workloads such as running, swimming, cycling and rowing show a higher rate of OTS. The highly motivated and dedicated athlete is often the most susceptible as they will continue to train despite extreme fatigue. Females are also more likely to experience OTS than males, however there are no studies related to gender differences in overtraining. Single sport specialization in the adolescent athlete often leads to overtraining and overuse injuries. Those young athletes who participate in a variety of sports involving different body parts have fewer injuries and are less susceptible to overtraining. Excessive training alone is rarely responsible for OTS without having personal, medical, or psychological stressors. Monitoring training loads and allowing for sufficient recovery is the best way to prevent overtraining. Should overtraining occur, more recent evidence shows that proper nutrition and low-level exercise may help speed recovery, with an emphasis on gradual return to volume rather than intensity. [89]

Overtraining or staleness is one of the most feared complications in competitive athletes. While some coaches think that it is necessary to force a short-term over-reaching as part of training, consensus is that this should be avoided because of the unpredictable nature of the results. Parameters for diagnosing overtraining include evaluating resting HR, HRV, creatine kinase levels and T-cells. During training, blood lactate, HR, respiratory exchange ratio (RER) and RPE levels can be used to determine OTS along with performance results. However, a need for consistent and measureable tools still needs to be explored. [26]

Monitoring training load is viewed as an important tool to determine how the athlete is adapting to their training and to minimize the risks of illness, injury and overreaching. This data can be used to examine load-performance relationships for future training and to determine readiness for competition. One of the concerns with overreaching is an increase in fatigue, a failure to complete a once achievable task, which brings about a concern in using maximal testing as a marker of overreaching as the fatigued athlete may lack the motivation to perform and testing may add to existing fatigue. Little information about the athlete can be determined from maximal testing in terms of overreaching. Monitoring of training load should include external load, such as speed, power and neuromuscular function while internal load monitoring should include RPE, HR, lactate, HRR, HRV, questionnaires and sleep. Current practices for monitoring often include combinations of these factors. In team sports the monitoring can be more challenging due to the diverse training activities, the influence of team tactics, playing time, position and social factors. Typically athletes involved in individual sports such as cycling, swimming and triathlon are more involved in load monitoring and are utilized in many of the research protocols, however it is important to monitor team sport athletes individually as well. It is also important to consider the smallest worthwhile change (SWC) and typical error to allow confidence prior to acting on any observed changes. Using appropriate scientific principles and accurate monitoring of training can help reduce the risks associated with negative outcomes. This will help the athlete to maintain optimal physiological and psychological health. [61]

A prospective study of male European professional football players (n=22) was done to examine the contributions of stress and recovery variables as assessed by the RESTQ-Sport to the risk of injury. It was hypothesized that high stress and low recovery values in the recovery- and stress-related scales would increase the risk of a later injury. Injury was defined as occurring during a match or training and leading to an absence of the next training session or match (time loss injury). Both traumatic and overuse injuries were considered together because of the low number of injuries and time loss due to illness was also document but was excluded from statistical analysis. The RESTQ-Sport was administered monthly, two days before the first league match of the month. Injured players did not take the questionnaire during an injury and the results from their previous questionnaire were used as predictors. The RESTQ-Sport scales served as the independent variables and injury risk was the dependent variable. The general stress scales for Fatigue (P=0.007) and the sport-specific scales Disturbed Breaks (P=0.047) and Injury (P<0.001) were significantly positively related to injury risk. In addition, low values on the Sleep Quality scale were associated with a higher risk of injury (P=0.01). Acute stress and coping ability were predicted to contribute to injury risk by the model. Muscle stiffness and feeling to be prone to an injury were highly related, indicating a potential relationship between how the athlete feels subjectively and their concern about injury. Based on the fatigue, sleep quality and disturbed breaks having a strong association with injury, cognitive and concentration deficits were a potential concern for the increased risk of injury. While this longitudinal study provided evidence of stress and recovery relating to injury in professional athletes, no training data or physiological data was used to support the findings. [90]

In order to identify physiological, cognitive and biomechanical parameters that could potentially identify athletes at risk for overreaching or OTS, well-trained triathletes underwent an overload training program. Subjects were divided into a control group (n=8), which maintained a training level and an intensified training group (n=16), which underwent a 40% increase in training for three weeks. Those in the intensified group who showed a decrease in performance at the end of the increased training load (n=11) were considered for a true overreaching group. The overreaching group demonstrated a significant decrease in performance from a baseline data collection prior to the intensified period ($P<0.001$). Following the overload this group demonstrated a decrease in HR and blood lactate concentration at submaximal intensities and at exhaustion ($P<0.01$). Cognitive changes were assessed using the Stroop test during exercise with a significant decrease in performance at exhaustions for the overreaching group compare to the control group ($P=0.04$). Biomechanical parameters were not significant. Further discriminant analysis found that change in HR and blood lactate were the most important factors to discriminate between control and overreaching, consistent with changes in the autonomic nervous system and a downregulation of the sympathetic nervous system. Cognitive changes were only apparent at exhaustion and subjects in the overreaching group also had a large increase in perceived fatigue at rest whereas there was no variation in the control group. This seems to support the theory of central fatigue in OTS as the cognitive deficits occurred at a slower running speed compared to baseline levels and those in the control group. However, physiological parameters still showed to be the most discriminant factors in overreaching and have the potential to be the best determinants of OTS.   [54]

A slower HRR is associated with impaired recovery and can be a potential marker for functional overreaching in athletes undergoing endurance training. Experienced triathletes were divided into training groups of control, no change in training, (n=10) and overload, overload training, groups, with those in the overload group who preserved performance level being considered for an acute fatigue subgroup (n=11) and those who decreased performance being considered in the functional overreaching subgroup (n=10). During the overload period, those in the functional overreaching group had a larger decrease in peak HR compared to the control and acute fatigue groups. At the midpoint of the overload period, the functional overreaching group had a large increase in HRR and a reduced peak power output (demonstrated by a lower peak HR). These were suggested to be from a decrease in central command, reduced chemoreflex activity from a lower accumulation of metabolites post-exercise and a change in the ANS control during immediate recovery. Following the taper phase, however, HRR was restored to baseline values. Neither the control group nor the acute fatigue group had any clear changes in HRR. By utilizing information about fatigue state and training phase along with HRR, a more complete perspective for monitoring training may be achieved. [91]

It has been estimated that 20% to 60% of athletes experience overtraining at least once in their career. Since the only effective cure for OTS is complete rest for several weeks or months, prevention is of utmost importance. It is argued that usable markers should be objective, not manipulable, applicable in training, not too demanding for the athlete, affordable and based on sound theoretical framework. It is hypothesized that psychomotor speed is reduced in athletes with OTS. Overtrained athletes often report concentration problems, cognitive complaints and memory problems. Computerized tests such as the Stroop Color Word Test have been used to compare healthy athletes and those with OTS. The preliminary evidence for psychomotor speed as an early marker for OTS is promising. [92]

Instead of considering the athlete as overtrained, a more appropriate terminology may be underrecovery as overtraining is a product of both the work-out and the failure to recover. Training recovery is believed to hold promise for improving performance even more than the short term recovery between training sessions or the immediate recovery such as that between sprints or sets. Regardless of the type, adequate recovery is expected to improve total work capacity and in turn future performance. Improved performance is typically assumed to be the best marker of recovery, confirming that the recovery modality has indeed done its job. However, other indicators of recovery seem to be much less useful, especially if performance is not improved. Because both training and recovery are different for each athlete, it is difficult to use the current research model to evaluate both effectively and make general statements that will hold true for each athlete. In many cases the changes with a recovery modality fail to reach significance leading many researchers to declare that they do not work even if the athlete shows improvements in subjective measures. Few of the studies utilize a long-term measure therefore it is difficult to translate improvements from short-term or immediate recovery to improvements in training recovery. Additionally, research models make it difficult to individualize the recovery needs of the athlete. Coaches and athletes would need to seek out different recovery techniques to be effective for the individual athlete in order to prevent overtraining. [41]

The avoidance of overtraining and the achievement of optimal performance can only be realized when athletes are able to balance training stress and recovery. Overtraining is not only from training errors but also from a high frequency of competitive events that do not allow for sufficient recovery. Symptoms of overtraining include depressed mood, general apathy, decreased self-esteem, impaired performance, restlessness, disturbed sleep, weight loss, loss of appetite, increased resting HR and increased vulnerability to injury. Recovery depends on the individual athlete, their training and situational conditions. Types of recovery can be passive, active or pro-active. The scissor model has been proposed to explain the balance of the demands between stress-states and recovery. As the stress-state increases, recovery must increase proportionally in order to avoid overtraining. Optimal performance is associated with a balance between stress and recovery. Monitoring the stress and recovery levels can be done using questionnaires such as the RESTQ-Sport, which evaluates seven general stress scales, five general recovery scales, three sport-specific stress scales and four sport-specific recovery scales. The RESTQ-Sport has been validated with a 24 hour test-retest reliability of all general scales as high ($r>0.79$) and has been used in various sports and for various nations. Changes in training volume as well as stresses in the life of an athlete have been reflected in the RESTQ-Sport. The RESTQ-Sport is also sensitive to modifications in the training schedule throughout the course of a training program. Athletes who completed the RESTQ-Sport six times over the course of a 24 week training period reflected conflicts and pressures that increased over the preparation phase and throughout the season, peaking before championships and declining during the tapering phase. The RESTQ-Sport however does not provide the final diagnosis of overtraining but is better suited to identify those at risk for overtraining when combined with the other indicators of overtraining. [38]

The RESTQ was developed to measure stress in a general sense and therefore supports a conceptual framework of overtraining and recovery along with other parameters. It is unclear how non-physiological, non-training stresses will affect the athlete in relation to the overtraining spectrum. If psychological and social stress factors are high amongst an athlete, the cumulative effect of overtraining may prevail. An imbalance in the total stressors, training and non-training, with diminished total recovery may lead to negative overtraining. Treatment of the stressors should be matched with interventions related the cause. For physical stressors, active rest, massage, yoga and stretching during the day and increased sleep at night would be appropriate. Mental training, relaxation, counseling and massage are potential strategies as interventions for psychological stressors. While training requires periods of intense activity, which may result in increased physiological stress, if it is met with adequately matched recovery, the athlete would be able to better tolerate the increase in stress. [45]

For classification purposes, OT research can be divided into single stressor and multistressor approaches. Single stressor research focuses on too much training and/or insufficient recovery as the cause of OTS whereas the multistressor approach suggests that excessive life stressors along with training stressors are the cause of OTS. It is believed that overtraining begins with a state of overreaching as a short-term maladaptation. Overreaching can be either a functional overreaching, responses to an incremental increase in training load, or a nonfunctional overreaching, a state of more chronic maladaptation, with signs of training distress, including performance declines and psychological disturbances. It is the prolonged maladaptation that leads to OTS. Markers of OT are mostly physiological parameters, but none stand out as a single predictive marker. Also the research on various overtraining studies lack a standardized approach. Performance may be considered the gold standard for the diagnosis of overtraining, however it is often difficult to distinguish between functional and nonfunctional overreaching using only performance as a criteria. It is impossible to ignore additional life stressors that may become part of overtraining and controlling for those stressors is not possible in most research studies with athletes. Therefore an integrated approach that emphasizes an exposure to various stressors as potential causes of OT should be utilized. Measuring stressors, performance and physiological responses will result in more knowledge about stress-related processes such as OT and can help contribute to timely identification by athletes and athletic trainers. [40]

Various hypotheses have been proposed as the cause of OTS, however for the most part each explains only one aspect. Most investigators do agree that OTS is related to an increase in volume and/or intensity of training or a consistent volume of high training over an extended period of time with insufficient recovery and that there is an association between injury and OTS. Mild tissue trauma is an integral part of training and with appropriate recovery the body will heal with improved performance via adaptive microtrauma (AMT). Without sufficient recovery, such as with OTS, a more diffuse, widespread, low-grade trauma more similar to an overuse injury may occur and it is this that directly impacts performance. The presence of inflammation in the body can be the cause of the psychological changes in mood and behavior and cell-mediated immunity may be compromised, rendering the athlete susceptible to infection. Most of the changes occurring with OTS should be regarded as adaptive in that they promote withdrawal from activity and encourage rest and recuperation. [93]

In endurance sports, the metabolic aspects of training fatigue appear to be the most relevant parameters to characterize overtraining, with a combination of inadequate recovery and dietary habits that do not allow for replenishment of substrate stores. To optimize training it is very tempting to reduce recovery periods with an increase in training as long as fatigue is bearable, however this combination can lead to an increased risk of overtraining. Endurance training loads of repetitive long-duration exercises are necessary to enhance the metabolic pathways for energetic supply to skeletal muscles. Myocyte alterations induced during intense exercise either via mechanical or metabolic pathways. An imbalance between reactive oxidative species (ROS) actions and antioxidant defense capacities of skeletal muscle has been suggested to be a potential factor in overtraining occurrence. It seems unlikely that overtraining might appear as a consequence of successive alterations in the skeletal muscle system, but rather that skeletal muscle cell damage may participate in the overtraining process. During endurance exercise, as glycogen stores are depleted and/or there is a failure in glycogenolytic metabolic flux, fatigue may induce a transient hypoglycemia. If glycogen depletion is chronic, and carbohydrate (CHO) intake is not adequately increased, subsequent performance will be diminished. Long-term glycogen depletion can lead to an increase branch chain amino acid (BCAA) oxidation, which is more likely to be responsible for a central fatigue process. However, ingestion of BCAA during or after endurance exercise has not been shown to significantly improve loss of performance due to metabolic fatigue induced by glycogen store depletion. But the link between BCAA oxidation during training exercises and serotonin secretion is a factor that may increase susceptibility to OTS when combined with other central or peripheral fatigue factor inducers. No metabolic parameters may be considered individually as a standard for the diagnosis of OTS and no study has been able to define the shift towards overtraining in endurance athletes although variations in energy metabolism appear highly relevant. [94]

One single bout of physical exercise of sufficient intensity and duration generates ROS, however continual training has been shown to enhance antioxidant status and decrease the generation of ROS. Conversely, overtraining results in impaired antioxidant capacity and increased oxidative stress, a state in which the production of ROS overwhelms antioxidant defenses. Increased oxidative stress and disrupted redox balance in response to heavy physical training has therefore been hypothesized as a predisposing factor and marker for overreaching. Male Soldiers were evaluated for physical performance (maximal and submaximal testing), and oxidative and antioxidant status three times during an eight week basic training sessions with the psychological makers, via questionnaire, determined five times during the same duration. During this time period at least three of five overreaching criteria were met by 31% (n=11 of 35) of the subjects. The criteria included: a reduced VO_{2max} of >5% or non-performance of the test; an increase in mean RPE during submaximal exercise >1.0 from the lowest value until the end of basic training; increase in somatic symptoms of OTS >15% from weeks 4 to 7 remaining the same or increasing from weeks 7 to 8; admitted feeling physically or mentally overloaded weeks 7 or 8; sick leave >10% of daily service, which was the upper third of all sick leave. As day activity time increased and rest time decreased during the first four weeks of training, all 35 subjects showed a decreased oxidative stress at rest, explained by either attenuated generation of ROS or enhancement of tissue protections and antioxidant systems because of adaptations to regular exposure to a small amount of ROS. During the second half of the training, although activity and rest remained constant, the training load was too strenuous causing oxidative stress. These results suggest that increased oxidative stress may be associated with overreaching during longer duration, over four weeks, of training. [95]

Two general models are used to study overtraining in athletes, assessing the athlete at various times throughout a competitive season, comparing physiological and psychological responses during training levels, and intentionally intensifying training to levels of overreaching for up to four weeks and examining physiological and psychological variables before and after this training session. While it has been difficult to establish prevalence of overtraining, those thought to be at risk are endurance sports requiring high volume intense training for four to six hours per day, six days per week for several months with minimal time off. It is easier to identify the symptoms of overreaching in the short duration studies compared to long-term studies, however the dramatic increase in training during these studies does not adequately represent a normal increase in training load. Theses studies can only be done for a short period of time and do not adequately reflect upon non-training stresses, which are believed to contribute to OTS, though the mechanism is unclear. Athletes that have OTS typically show a decrease in performance, a decrease in maximal HR, lower maximal blood lactate concentration and frequent illness such as upper respiratory tract infections. Because the best indicators of OTS, poor performance and persistent fatigue, occur too late to be a benefit to the athlete, early predictors or indicators are needed. Preventing OTS should be the focus and can be done using routine monitoring of training logs, performance, HR after standardized maximal effort and athlete self-analysis of stress, fatigue, sleep and soreness. [43]

A systematic review of literature was done in order to determine if subjective measures accurately reflect changes in the athlete's well-being and whether these measures are responsive to acute changes in training load and chronic changes. The most commonly used subjective measures in the studies were the POMS, RESTQ-Sport and Daily Analyses of Life Demands of Athletes (DALDA). The findings support the use of subjective measures to accurately reflect acute and chronic training-related changes to the well-being of the athlete. The RESTQ-Sport accurately reflected measures of perceived stress and recovery and seems to be useful in monitoring these levels. The POMS was useful in measuring mood disturbances while the DALDA was useful in measuring symptoms of stress. Within the studies, subjective measures were more sensitive and consistent compared to objective measures, including comparisons between and within studies. As for performance measures, VO_2max had a moderate relationship with subjective measures, perhaps indicating a psychological readiness to perform as opposed to an improvement in physiological measures. Of the questionnaires examined, only the RESTQ-

Sport was responsive to both acute and chronic training load with the fatigue (stress) and physical recovery, general well-being and being in shape (all recovery) subscales responding to both types of training. Because of the superior responsiveness to subjective measures over objective measures, there was negligible evidence for an association between the two measures. However, the majority of the studies had a small subject size and the objective measures may not reflect the smallest worthwhile change. [53]

A comparison was made between a systematic literature review on monitoring training loads of endurance athletes and a focus group discussion with coaches to see how the scientific literature meshed with the coaches' requirements for monitoring training. Training load can be calculated a variety of ways and most often utilized some combination of duration, RPE and HR. Long-term HRV monitoring is another reliable measure, however results are highly individualized and cannot be applied to every athlete. Blood lactate concentrations has the disadvantage of involving blood draws and being invasive. Hormones and proteins can potentially be analyzed via saliva, however further research is needed into the methods. Subjective self-reported scales and questionnaires, when combined with physiological measures seem to be the most applicable method. Coaches agree that this combination is most relevant, however they would like only the most relevant information given to them. Therefore, it was suggested that a database that can collect and analyze the essential information for the coach and athlete would be most beneficial. This, however, has not been developed and would take time to accomplish. [86]

The pre-season training phase for athletes is often designed with an immediate increase in training load in order to prepare the body for the upcoming season. One of the challenges of this time period is to provide enough stimuli to create physiological change without inducing an overreaching or overtraining state. During an intense 14 day pre-season training camp, 18 professional Australian Rules Football players underwent the documentation of various physiological and psychometric variables to examine their usefulness for monitoring training responses during their normal training camp period. Training load, calculated by the product of the training session duration (minutes) times the session RPE, showed significant daily variations ($P<0.001$). The changes in training load were related to day-to-day changes in exercise heart rate, log transformation of the standard deviation of successive R-to-R intervals (LnSD) and changes in individual wellness based on the large to very large correlations. As expected mood and training load were negatively correlated, the larger the training load the worse the wellness score was the next day. While acute training load is expected to result in an increase in sympathetic activity, daily exercise heart rate decreased and LnSD increased during this period of time. Since fitness changes do not occur with one session, it was recommended that these measures be monitored over a week before making any distinct changes to training. It was also recommended to monitor daily training loads along with physiological variables over the course of a week or more in order to better assess the training. Despite high training loads, the athletes coped well with the demands, displaying an increase in performance measures and an absence of injury. [87]

The stress and recovery of elite Olympic rowers (n=6 female, n=5 male) was monitored during a high-altitude preparation camp. The rowers completed the RESTQ-Sport on a regular basis as a subjective monitor of their recovery and stress levels over the training camp. It was hypothesized that increases in endurance training would lead to higher stress levels and lower recovery levels with the opposite effects being reflected during the decrease in endurance training. For these athletes as the average number of minutes of daily extensive endurance training increased the trend for somatic components followed course. The greater the time spent in training, the greater the stress. However, the subjects also had an increase in social relaxation during this time as it included various team-building activities of training camp. In comparison of performance results the athlete in the boat that won a medal had a more positive recovery-stress state as indicated by lower scores of fatigue, lack of energy and somatic complaints. The results for fitness/being in shape, burnout/personal accomplishments, self-efficacy and self-regulation were higher than for a rower that finished 13th. These results give a clear picture of the events of the past few days for the subject than the more generic POMS, which just assesses current mood state without giving an indication about potential intervention. [51]

Physiological parameters of HRV, BP variability and baroreflex sensitivity were used to potentially detect overtraining in 10 healthy athletes during a two week training camp. During that time training, sleep and mood (via POMS) were monitored. Subjects underwent two daily training sessions, a morning stepwise cycling test in the morning and afternoon running for 40 minutes and cycling for 80 minutes, both at 85 to 90% of their anaerobic threshold. These loads were above the normal level to which they were adapted. During the training camp there were significant decreases in performance (P<0.05) with recovery performance returning to above the baseline levels (P<0.01), indicating that subjects were in an overreaching state with a supracompensation after recovery. Physiological variables were assessed prior to training camp, at the midpoint of training camp and a few days post-training camp. Mean HR increased significantly during training camp and then normalized during recovery. The only HRV variable to change significantly during training was RMSSD, which was reduced with the increased training before recovering. Baroreflex sensitivity was reduced with the increased training yet there were no changes in BP variability. The only POMS variable that was significantly different was vigor, which had significant difference between pre-training and recovery measurements and between the mid-point and recovery measurements ($P<0.05$). Accompanying the change in vigor was an inverse but not significant increase of fatigue. There was an indication of increased sympathetic activity with the overload of training, however the study involved a very low sample size and lacked of gender specific analysis. Also the POMS scores were not consistent enough to show change. [96]

Even though it is believed that sleep disruption could compromise athletic performance, the effects of sleep loss on athletic performance is poorly understood. A neurometabolic theory suggests that sleep assists in recovery of the nervous system and the metabolic cost of a wakeful state that occurs with the non-rapid-eye movement (NREM) sleep time. Time spent in this cycle seems to be important for the preventing some of the causes of OTS. There is not enough information on the effects of elite training on the quantity or quality of sleep in athletes. However, it has been reported that university students demonstrate poor sleep patterns and suffer from chronic sleep problems and disruptions. It is therefore important to distinguish if it is the stress of athletics versus the stress of being a college student that is leading to sleep disruptions. Sleep disruption, characterized as a loss of sleep, is associated with increased sympathetic and decreased parasympathetic cardiovascular modulation. Whether this is a result of the OTS status of the athlete or contributes to the status cannot be determined as there is no research available on the effects of chronic training adaptations on sleep. Preliminary evidence does suggest that a functional over-reaching state is associated with sleep disturbances. [63]

It was proposed that the physical and psychological demands of military training resulted in a significant prevalence of overtraining symptoms such as fatigue and underperformance which was concerning because of the increased risk of injury associated with the effects of overtraining. Physical fitness, physiological, psychological and biochemical measurements were taken throughout a 45 day Australian Army Common Recruit Training course. The recruits experiences symptoms of overtraining during this time. The negative psychological symptoms including mental fatigue, sleep disturbances and confusion were evaluated via questionnaire. Accumulated sleep deprivation was believed be a major contributor to the overtraining effect. While performance did not deteriorate considerably, Soldiers had a less than desired improvement in overall fitness. The increase in minor infections based on a decline in immune function was believed to be the greatest risk of overtraining during this period. A conclusion was made that a minor adjustment in the rest schedule could be used to prevent overtraining in these Soldiers. [42]

The cardiovascular response to functional overreaching via prolonged overtraining was monitored in well-trained male triathletes. Subjects were divided into a control group (n=11), and an overload training group (n=24) with those in the overload group who experienced a decrease in performance, followed by a supercompensation were then put into the functional overreaching group (n=12). Those in the functional overreaching group demonstrated a decrease in cardiac output after the overload period, which returned to pre-training values at the post-training data collection session. These decreased values were associated with a decreased heart rate and stroke volume at mid-training. The cardiac response was attributed to the reduced adrenergic response to intense exercise from a downregulation of the sensitivity of the sinus node's β-adrenergic receptors to norepinephrine. Subjects in the functional overreaching group also had a decrease in performance and lower VO_2max suggested to be related to the decrease in cardiac output and a lowered capacity to produce energy at the muscular level. All of the subjects did return to pre-exercise levels following taper period. [46]

Athletes in a normal training cycle will undergo bouts of increased activity in order to improve performance. These athletes will recover normally from training stress within a few weeks of appropriate recovery, will see improved performance and should be considered in a state of overreaching. The term overtraining is proposed to be reserved for those athletes who take months or even years to recover from a training load and also experience more severe changes fatigue and mood, however there is no scientific evidence to confirm or refute this. Some problems with overtraining studies include the following: cross-sectional studies of athletes are rare, studies on overtraining lack evidence on the development of overtraining, performance levels are often not included and information on the symptoms are either lacking or inconsistent. Performance based studies intended to induce an overreaching state lack consistency in the measurement of decreased performance and if the intervention actually led to a decline in performance. It is also debatable how well laboratory-induced exercise to fatigue can accurately reproduce the environment of competition. Changes in mood state are a clear indication of overtraining, however increases in the global POMS scores during periods of increased training do not always result in an overtrained state and would need to be combined with an objective measure. Autonomic nervous system changes resulting in parasympathetic overtraining, as characterized by increased fatigue, apathy and altered mood state is most frequent and represents the current form of overtraining. Measures that examine the balance of the ANS are the most appropriate physiological markers of OTS along with performance and subjective information from questionnaires and information about the quality and quantity of training and recovery. This information will help to differentiate between the overreaching necessary to provide physiological adaptations and the accumulation of training and/or non-training stress that leads to overtraining. [55]

The pre-event taper is a particular phase of the training cycle where there is a reduction in the training stresses in an effort to allow for physiological and psychological recovery with the goal of peaking for competition. Cardiac changes do not typically occur with the taper. Resting HR, submaximal exercise HR, maximal exercise HR, BP and cardiac dimensions either do not change with taper or the changes that are reported in the literature are inconsistent. Hormonal changes during the taper, especially testosterone and cortisol levels also have inconsistent findings in the literature. It may be the influence of the hypothalamus in integrating the different stress influences among the ANS and the endocrine system that affects the hormonal response. Physiological changes alone cannot explain the performance changes in athletes following taper. As positive performance changes have been accompanied by positive changes as indicated by the REST-Q Sport, the stress accompanying training may or may not be solely training related. Tapering has been reported to induce positive mood changes based on the POMS questionnaire. Typically decreased levels of perceived fatigue, depression, anger and confusion accompany increased levels of vigor during the taper period. The elevated tension related to pre-performance anxiety may be revealed in accompanying physiological data explaining the lack of or inconsistent change in cardiac variables. The training changes with the taper are often accompanied with a decrease in RPE. This inverse relationship between HR and RPE means that the greatest improvement in performance following taper accompanies a decrease in HR for a given RPE. Forced reduction in activity and increased rest time also relate to an improvement in the quantity of sleep to help reduce fatigue. The fatigue and adaptation model associate the taper with recovery of physiological markers that had previously been impaired. [59]

While many studies offer information about training strategies to enhance performance with the goal of forestalling fatigue, leading to decreased performance and increased risk of chronic injury, few have actually linked injury to perceived training intensity and fatigue to injury among college athletes. A survey instrument was used to obtain information from current NCAA Division II athletes (n=149) about training frequency, training intensity, injury incidence and feelings of exhaustion and apathy. The female athletes (n=68) surveyed showed a significant negative relationship for chronic injury incidence and noncompetitive season physical exhaustion (r=-0.33, p<0.01) while the male athletes (n=81) surveyed had a significantly negative correlation for incidence of acute injury and vigorous intensity training (r=-0.22, p<0.05). Increased physical stress, related to overreaching or overtraining, puts the athlete at risk for fatigue, which can lead to chronic injury. While the results were not significant, 44% of the male athletes had a chronic injury in the previous 12 months. The female athletes had a significant positive correlation for noncompetitive season physical exhaustion and vigorous-intensity training (r=0.24, p<0.05) while male athletes had a significant positive correlation for competitive season physical exhaustion and vigorous-intensity training (r=0.57, p<0.01). The female athletes had significant positive correlations for competition season mental exhaustion and physical season (r=0.666, p<0.01) while male athletes had significant positive correlations for competition season mental exhaustion and vigorous-intensity training (r=0.421, p<0.01), competitive season physical exhaustion (r=0.456, p<0.01) and noncompetition physical exhaustion (r=0.267, p<0.05). Both mental and physical exhaustion are signs of overtraining and are a cause of decreased performance in athletes and these results highlight the need for more rest or recovery in the training program. Daily activity logs were suggested to track the RPE of the practice that day as well as assessment of acute mental and physical fatigue as ways to monitor training and allow for increased recovery. [56]

A prospective study aimed to measure the effect of recovery and stress on illness and injury for 53 elite youth soccer players. The medical staff tracked injuries and illnesses using the definition set forth by FIFA as "any physical complaint sustained by a player that results from a soccer match or soccer training, irrespective of the need for medical attention or time loss from soccer activities." Injuries were reported based on the inability to take part in a training or match, receiving medical attention for more than one day even with full participation. Time loss injuries were divided up by the number of days missed. Additional categories were used for overuse injuries caused by repeated trauma and traumatic injuries resulting from a specific event. Illness was distinguished by the symptoms presented. Physical stress was measured by the sum of the duration of training and matches and each player's RPE for the session. The product of the duration and the RPE for each session was defined as the training session load. Psychosocial stress and recovery were monitored using a monthly administration of the RESTQ-Sport. Physical stress was related to traumatic injuries but not overuse injuries. The weekly duration over the preceding week was higher for those with an illness than for those that were healthy. No clear relation was found between specific components of the RESTQ-Sport for stress and recovery and the occurrence of injury but the subscale for fitness/injury was significantly higher for those with an overuse or traumatic injury. Illness was related to the general stress, emotional stress, fatigue, social recovery, general well-being, and sleep quality scales. Monitoring stress, recovery and training on a daily basis gave better insight into the players at risk for illness and injury. This gives insight into future studies for monitoring training load and subjective factors. This study could be strengthened with the addition of physiological variables and a calculation of the SWC for training load that would put someone at risk for illness and injury. [60]

The research about overreaching, overtraining and effective recovery typically focuses on individual athletes involved in professional and endurance sports, however the majority of youth and collegiate athletes are involved in team sports [46, 51, 54]. Multiple subjective tools exist for assessing the mood and stress levels in athletes with the POMS and RESTQ-Sport being the most popular [24, 38, 45, 51, 53, 90]. Physiological variables that can be monitored for assessing stress include HR, HRV, BP and blood lactate [24, 52, 61, 89]. Additional daily monitoring can include training load, RPE, sleep and fatigue levels [53, 56, 59, 86]. However since subjective and objective variables have not been validated against one another, more research is needed to determine the appropriate method to determine OTS [24, 26, 53].

Heart Rate Variability

Standards of Measurement

Heart Rate Variability (HRV) is the ability of the heart to modulate the interbeat intervals as well as the oscillations between consecutive instantaneous heartbeats [1, 2]. Heart rate (HR) is initiated via the sinoatrial (SA) node with action potentials being generated at a fairly consistent frequency in healthy individuals [2]. The autonomic nervous system (ANS) regulates HRV occurs through parasympathetic and sympathetic pathways making HRV analysis an appropriate non-invasive method for analyzing the ANS [2-4]. Changes are communicated from the medulla via the vagus nerve for parasympathetic changes and sympathetic efferents for sympathetic changes [4]. In general parasympathetic activity decreases HR by releasing acetylcholine thereby increasing the threshold of the SA and the variability between successive R to R intervals while sympathetic activity and the presence of epinephrine increases HR and decreases HRV [3, 4]. Analysis of HRV can be done with the analysis of electrocardiographic

(ECG) recordings using readily available software for the computer and has been developed for smart phone applications using photoplethysmography (PPG) [3, 62, 64].

Heart rate variability is evaluated using time domain and frequency domain measures. Time domain measures determine the rate between successive normal-to-normal (NN) intervals between the peaks of successive QRS complexes (R-R intervals). The calculation of statistical time domain measures includes standard deviation of the NN interval (SDNN). As this measure equates to the square root of variance, it is also equal to the total power of spectral analysis and therefore reflects all of the cyclic components responsible for variance. The square root of the mean squared difference of successive NN intervals (RMSSD) and standard deviation of the average NN interval (SDANN) are other commonly used statistical measures. With time domain measures, it is important to only compare measurements taken over similar time periods as long-term (24 hour) and short-term (5 minute) intervals cannot be compared. Frequency domain measures, a function of how power (variance) distributes as a function of frequency, are calculated as non-parametric and parametric. The non-parametric fast Fourier transformation (FFT) method employs a simple algorithm and a high processing speed while the parametric autoregressive (AR) method has a smoother spectral component, which can be distinguished independently of preselected frequency bands. Short-term recordings of two to five minutes consist of very low frequency (VLF), low frequency (LF) and high frequency (HF) components, with the LF and HF varying in relation to changes based on the modulations of the ANS. The HF component is driven by vagal activity while the LF component in normalized units (nu) is considered to be a marker of sympathetic activity by some and as a parameter of both sympathetic and vagal activity by others. The LF/HF ratio is then considered to be either a reflection of the sympathovagal balance by those who consider the LF to be sympathetic and to reflect sympathetic modulations if the parasympathetic is reflected in both the LF and HF components. Measurements are typically made in absolute values of power (m^2) or nu, representing the relative value of each component with the VLF removed. Standardization of the ECG recordings is paramount for research, especially studies investigating clinical applications of HRV. For short-term recordings, frequency domain measures are preferred over time domain measures with recordings lasting at least 10 minutes and a minimum of five minutes being used to assess the HF and LF components and minimize error. In addition, manual editing of RR intervals will also reduce the chance of error. Larger prospective studies are needed to determine values for various age and gender subsets. [1]

It is often implied that the heart beats a constant rhythmic rate however low HRV is can be used as a marker for cardiovascular disease. The importance of HRV is highlighted in cardiac transplant patients where denervation leads to a reduced HRV. In normal circadian rhythm patterns of the body the ANS will contribute to circadian HRV patterns, which appear on the spectrum as ultra-low frequency. Thermoregulatory effects of the body affect the VLF waves and fluctuations in body temperature during illness or injury would need to be considered. The sympathetic nervous system activity, which accelerates heart rate, can only affect the LF components of HRV while parasympathetic nervous system activity can modulate both LF an HF components. Because of the different frequency response characteristics of sympathetic and parasympathetic nervous systems on HR modulation, analysis of HRV is often used to determine autonomic balance. [2]

The HF components of physiologic HRV are predominantly modulated by the parasympathetic nervous system whereas the LF components are under the influence of both the parasympathetic and the sympathetic systems. However these specific spectral components should not be used as measures of autonomic tone. The efferent vagal impulses of cardiac parasympathetic tone have higher intrinsic frequencies than that of the HF component of HRV, which corresponds to the modulation of vagal tone. It is the modulations of vagal efferent activity, not the tone that causes the alterations that increase the HF components of HRV. Therefore when the SA node becomes saturated with AcH although there is still a corresponding decrease in HR, the overstimulation causes constant vagal activity, which does not alter the interbeat intervals and leads to a diminished HF. Physiologic modulation of the sympathetic tone is driven by vaso- and thermocontrol regulatory mechanisms therefore while moderate exercise will increase the sympathetic tone within a physiological range, maximal exercise will lead to a saturated sympathetic tone, losing the potential of being modulated by the subtle physiologic control mechanisms. It is thereby correct to associate the frequency domain measures with modulation of ANS tone but incorrect to assume that it represents a particular shift in ANS tone from sympathetic to parasympathetic. [10]

Changes in HF come from respiratory modulations such that parasympathetic activity increases in exhalation and decreases with inhalation. In order to evaluate the magnitude of the fluctuations in parasympathetic activity the vagus nerve in anesthetized, vagotomized and spinal cord anesthetized dogs underwent either constant or fluctuating stimulation and the resulting power spectral components of HRV were analyzed. Constant frequency vagal stimulation increased HRV slightly however when adjusted for mean RR intervals, the changes in TP and HF were not statistically significant. Moderate and strong modulation increased the total HRV and the HF components significantly before and after the RR interval adjustment. Strong modulation increased HRV and power HF significantly compared to control and moderate modulation when the mean RR interval was taken into account. It was concluded that the HF component is related to the magnitude of the fluctuations in parasympathetic outflow and not parasympathetic tone. [11]

The LF/HF ratio and normalized units of LF and HF are of interest because they are have been used to been purported to have a degree of interpretability between studies as proportional change in these values as well as allowing for direct comparison between AR and FFT. However this assumes some level of redundancy between the measures. Very rarely does the LFnu and HFnu calculations combined to represent 100% of total in the AR method. Also, a change in LF does not linearly correspond to a change in HF should the VLF measure or TP be used in the calculation. Therefore it is important to consider the calculations used in obtaining these measures before declaring that they are interchangeable between studies. The LF/HF ratio usually has a positively skewed distribution resulting in a log transformation of the measures for statistical analyses while the LF nu and HF nu are typically normally distributed. Because of the skewed distribution, the mean of the LF/HF is not identical to the LF nu and reporting just the normalized units or the LF/HF without considering the absolute power values will obscure the interpretation and is not recommended by the Task Force [1]. All of the HRV measures, time and frequency domain, show some degree of multicollinearity however the changes in HRV are not necessarily proportional. Changes in RMSSD are not necessarily reflected to the same level in HF power and significance with LF nu and not with LF/HF ratio does not mean that one is better at measuring sympathovagal balance. The nature of HRV is still not well understood and the ability to recommend a particular measure is beyond the scope of this review article. [12]

To test parameters that provide the best indicator of sympathovagal balance, the RR interval, time domain HRV measures of mean RR intervals, RMSSD, SDNN, pNN50 and the AR frequency domain measures of LF, HF LF/HF as well as the natural log of LF and HF, and a ratio of the RR interval to the intrinsic RR interval of the SA node were measured in healthy volunteers (n=14). The LF/HF ratio had the lowest r^2 value when the subjects were not included as a factor in the model, suggesting that it is not an ideal measure of sympathovagal balance while the natural log of the LF power was deemed the best predictor. The RR intervals serve as indexes of the net effect of the sympathetic and parasympathetic influence on the SA node but cannot provide assessment of overall autonomic tone. The most appropriate characterization of HRV is assessment of the modulation of the ANS. It cannot be used to determine autonomic tone. [35]

In order to assess the relationship between RR interval length and HR variability healthy subjects (n=83) underwent ambulatory 24 hour Holter recordings. Time domain measures included mean HR, mean RR interval length and SDNN. The parametric AR analysis was used for the frequency domain measures VLF, LF and HF. The mean RR interval length and corresponding HF power were analyzed in five minute segments over the 24 hour recording. The five minute values of HF power were plotted as a function of the corresponding mean RR interval values and a quadratic regression model was used to study the relationship between RR interval length and the magnitude of HF variability to determine if the relationship was linear or saturated. Saturation is considered to be the point when an increase in AcH levels no longer produces a change in the HRV response during inspiration, thereby blunting any changes in HF power. The majority of the saturation effect was seen during sleeping hours and subjects with a saturated relationship also had a tendency toward higher aerobic capacity as determined by a graded exercise. There was no consistency in the HR as some subjects were about 60 beats per minute while others were about 40 beats per minute. [97]

Initially HRV will increase as parasympathetic activity increases however there is a curvilinear relationship where HRV will decrease even with an increase in parasympathetic effect once a certain threshold is reached. Healthy volunteers (n=14 male, n=15 female) underwent resting baseline HRV data collection prior to pharmacological interventions to establish parasympathetic stimulation, parasympathetic withdrawal and intrinsic RR intervals. From each of the three sessions, five minutes of HRV was analyzed in relation to each subject's individual intrinsic RR interval values for the time domain measures of SD, RMSSD and pNN50 and the AR frequency domain measures of LF and HF with natural logarithmic transformation. Linear regression was used to explore the relationship between HRV measures and parasympathetic effect using both linear and quadratic model coefficients. In all cases the quadratic fit was better than the linear fit confirming that the relationship between HRV and the parasympathetic effect is best described as curvilinear with a decrease in HRV once a parasympathetic plateau is reached. For most individuals, peak RR interval value does not correspond with the peak HRV value. In situations where large quantities of AcH are released during expiration, a large enough dose of AcH will be present during inhalation thereby blunting the expected drop in parasympathetic activity. Without this drop in parasympathetic activity, there will not be any change to the HF power, demonstrating that the individual has low HRV. While this study confirms that the quadratic model is superior to the linear model, it does not confirm that the quadratic model is the best model with which to display this change. In addition, it is noted that the individual variations in HRV must be considered. [20]

During stress, such as the stress of exercise, the cardiovascular system makes dynamic adjustments in response to changes in heart rate and blood pressure. The use of ECG analysis allows for the measurement of the dynamic changes in the ANS via HRV measurements. The parasympathetic effects originate in the dorsal vagal nuclei of the medulla, are relayed through muscarinic receptors and modulated via the right and left vagus nerves that innervate the SA and the atrioventricular (AV) nodes, respectively. The sympathetic efferents also originate in the medulla but are mediated via alpha and beta adrenoreceptors and are present throughout the atria and ventricles. Exercise causes a withdrawal of the parasympathetic nervous system and an increase in sympathetic activity. Heart rate variability analysis can be used to analyze the stress of training and recovery. Changes in HRV with exercise are dependent upon the type of exercise, the intensity of the exercise, gender, age, prior training and current fitness levels. Any changes in HRV can be used to monitor training programs in order to prevent or diagnose overtraining or over-reaching states. [4]

Analysis of ECG data for time domain and frequency domain can easily be done via Kubios HRV software (ver. 2.1, Kuopio, Finland). Time domain methods are computed from successive R-R intervals and include SDNN, RMSSD and pNN50. In frequency domain methods, spectral estimates are divided into VLF (0-0.04Hz), LF (O.04-0.15Hz) and HF (0.15-0.4Hz) bands. From these bands normalized powers for LF and HF, LF/HF power ratio and total spectral power can be obtained. Kubios HRV supports both binary and ASCII text files of raw ECG data or R-R intervals. Once the data is run through Kubios HRV, artifact correction, sample selection and trend removal options can be utilized to filter the data. Artifact correction allows for correction on parameters that reflect HF variability and removal of peaks in the data can prevent artificially inflating HF power. Trend removal corrects removal of VLF when only HF and LF are of interest. This software is a solution for HRV analysis. [3]

The influence of the spectral indices of FFT and AR were compared on the characteristics of HRV in a seated resting condition (n=56) and during orthostatic stress (n=15) in healthy adults aged 18-66 using the criteria established by the Task Force [1]. All of the absolute values of the HRV indices calculated for both methods were significantly correlated ($P<0.01$). In the seated condition the AR and FFT produced significantly different results for HF power, HF nu, LF/HF ratio and TP. A Bland-Altman plot showed a large discrepancy for all HRV indices both seated and during the orthostatic stress conditions. This agrees with previous results that a strong correlation between the indices does not necessarily mean that they are interchangeable or can be used in direct comparison. The FFT overestimates HF and as the HF and LF components increase the difference between the two techniques increases as well. This could be related to the wide-band noise being isolated and suppressed by the AR that is then evident in the TP of the FFT analysis or because of the lack of clear separation in the bands by the FFT causing an overlap that increases the values of the LF and HF power. The AR could perhaps have an advantage in HRV assessment however more research is needed. [15]

In a comparison of healthy volunteers (n=9) and patients who had received a heart transplant (n=9), the FFT and AR methods of analysis were compared from five minutes of resting ECG data. Utilizing a paired *t*-test for statistical analysis between methods, there was no significant difference in the comparisons of LF measures however HF was significantly higher with FFT (p=.003) in the normal group. In the transplant group LF power was not measurable and while HF was higher with AR it was not significant. When the participants were pooled, the two techniques were comparable however any differences were at higher values of LF and HF power. The AR tended to underestimate HF and overestimate LF relative to FFT. [13]

The HRV results for seated and standing data were compared between two frequency ranges of FFT and the AR method in a large population (n=614, age range 25 to 89) of healthy and non-healthy volunteers. The LF and HF powers were lower with AR than FFT in both normalized and absolute units. Limits of agreement were wide with the AR measure of LF nu between -26% and +18% of the FFT value. The AR had higher LF/HF (p<.001) with the differences being more pronounced in the standing rather than the supine position. While the qualitative results of the two methods were deemed similar, the quantitative results were significantly different. These results would need to be taken with caution as the data were analyzed with different methodologies than those outlined in the Task Force [1] recommendations. [33]

There is no consensus on whether FFT or AR is the appropriate method for frequency analysis therefore the agreements between the two methods were examined during postural changes in healthy volunteers (n=8) as well as with patients with arterial hypertension and an experimental model of hypertension in rats and pharmacological blockade of the ANS in control rats. Approximately 43% of the data did not agree between the two frequency domain techniques and in the experimental models the LF component did not agree. The FFT method showed greater power in the HF component when both frequency domain measures were compared relating to an increase in the vagal indices. Normalized HF values were overestimated in FFT for the R-R intervals in normotensive and hypertensive subjects. The AR method showed a significant increase (P=0.042) in LF/HF ratio after postural change in the healthy controls, relating to an increase in the sympathovagal balance. Advantages of FFT are the simplicity of the algorithm, good reproducibility, and high processing speed. Advantages of the AR method are good performance in time series with reduced number of points, smooth spectral components making it easier to distinguish between the HF and LF components, easy identification of the central frequency of the component and an accurate estimation of power spectrum density even for a small number of samples. In pathological conditions both methods seem to be adequate measures of autonomic index estimation however the same conclusion cannot be made in healthy controls under orthostatic changes. [14]

The two frequency domain analyses cannot be used interchangeably or compared directly. The aim of this study was to assess the differences in LF/HF between the spectral methods and to determine the appropriate analysis under controlled breathing conditions. A paired *t*-test between FFT and AR showed significance (p<0.05) at four, seven, thirteen, nineteen, twenty-two and twenty-five breaths per minute. With paced respiration the AR is more of a disadvantage because the broader LF peaks overlap with the HF thereby increasing the LF/HF ratio. Therefore in paced breathing FFT is the preferred method of analysis. [16]

The sensitivity of the FFT and AR data processing were examined at rest, during submaximal and maximal exercise intensities and during recovery from maximal exercise for 16 healthy individuals (n=9 male, n=7 female). In addition, raw and normalized LF and HF powers were compared between FFT and AR using a paired Wilcoxon test. The FFT calculations of TP and HF raw power were significantly higher at rest (p<0.05) but there was no difference for LF raw power (p>0.05). During submaximal and maximal exercise TP in FFT was higher than AR while in submaximal exercise HF power, both raw and normalized, was higher in FFT compared to AR. Conversely, LF normalized power and LF/HF in AR was higher than FFT during exercise. During recovery LF powers did not differ but HF from FFT was higher and LF/HF was from AR was higher. The AR method was more sensitive to the effects of dynamic exercise but both approaches were insensitive to the increase in exercise intensity. As these two methods provide different results, they cannot be used interchangeably. Differences may depend on the intrinsic effects of exercise on the modulation of the ANS however no conclusion has been made about which is more appropriate in exercise or at rest. [17]

While an ECG recording is a valid tool for assessing HRV, it is not practical for field assessment and everyday use by athletes and coaches. With the prevalence of smart phones, applications have been developed for monitoring HRV data. The ithlete™ smart phone application underwent cross-validation with simultaneous ECG recordings to determine ultra-short-term RMSSD data in the supine position for 25 healthy college students. The RMSSD values were not significantly different ($p=0.91$), the effect size was negligible (partial $eta^2=0.001$) and correlation was near perfect ($r=0.99$, $p<0.001$, SEE of 1.47). Repeated trials were not performed and the ithlete™ is only capable of recording RMSSD data. However the ithlete™ values did mirror the values of traditional laboratory HRV data collection and smart phone applications may prove to be a valuable tool for HRV data collection in athletes. [64]

The ithlete™ HRV smartphone application was used to evaluate ultra-short the log-transformed root mean squared of successive R-R intervals (Ln RMSSD) measures across three weeks of off-season training load in female collegiate soccer players. Daily HRV recordings were taken in the supine and standing position after waking, however only the supine values maintained an acceptable level of relationship between HRV and training load. Additional self-reported data for sleep, mood, fatigue, stress and soreness was collected three times a week. The weekly measures of Ln RMSSD were more sensitive to training adjustments than the mean HRV values and daily fluctuations were greater during a week of high training load versus a week of low training load. Monitoring Ln RMSSD changes throughout training may provide an objective physiological marker to assess the individualized effects of training impact and adaptation. The average of a minimum of five consecutive days of recordings are recommended for effectively monitoring training. [62]

The Elite HRV smartphone application was compared to HRV analysis of RR intervals using Kubios HRV software. The Elite HRV application uses a personal HR monitor to collect RR intervals and extrapolate the data to compute HRV measures. In addition, the RR intervals can be exported and run through HRV analysis software such as Kubios. Data were log transformed and analyzed using a Bland Altman plot to assess Limits of Agreement and Pearson's Product moment correlation. While correlations were strong (r=.092; p<.001), a negative bias with larger discrepancies was identified. One of the concerns is that the entire sampling period for the Elite HRV must be used in analysis. While the participants were instructed to use a specific timeframe, if they lost track of time the data could not be edited. Previous research has indicated that the methodologies must be kept consistent included the time frame of recording. In addition, comparisons could not be made between artifact correction techniques, as the Elite HRV does not publish their artifact correction technique and level. The recommendation from this study was to use the RR intervals collected for analysis through known software such as Kubios and not to rely on the calculations from the smartphone application for research. However, as the Pearson's Product Moment Correlation was significant, it is possible that this application can be used for daily HRV measurements as long as comparisons are made only between the individual with this instrument. [73]

Smartphone technology uses an optical recording of the pulse wave, referred to as pulse PPG, as an alternative to ECG measurement for approximating beat-to-beat intervals for use in calculating HRV. At rest the smartphone pulse rate variability (PRV) system and ECG collections corresponded, however the smartphone overestimated the length of proportionally longer heart rate periods and underestimated shorter periods. Corrections were made using a z-score transformation. When a second experiment was utilized to examine the smartphone HRV analysis under physical and mental tasks, similar error was verified and again effectively corrected. The addition of tasks did not alter the accuracy of the system. This system provides an advantage over laboratory-based data collections especially when larger sample sizes are utilized. [67]

The PPG signals can be used to extract PRV as a potential surrogate to HRV. The main difference between PRV and HRV is the time in which it takes for the signal to travel from the heart to the arteries in the finger, called the pulse transit time (PTT). The variability in the PTT reflects the interbeat interval changes that are then noted by the PRV. The use of PRV in place of HRV was examined during a head-up tilt table test (n=17), going from supine for four minutes to head-up at 70° for five minutes and then back to supine for four minutes. Measurements of ECG and PPG were taken simultaneously. Similar indices were derived from the HRV and PRV measurements obtained from the ECG and PPG collections, respectively. Time domain and frequency domain indices derived from PRV had no statistically significant differences from those obtained with the HRV measurements ($p>0.05$) and there was a strong linear correlation ($p>0.09$). The supine indices had a higher similarity than the head-up position. The agreement between the physiological analyses of the PRV with the HRV makes it a plausible substitute. Slight differences occur, the PPG pulse wave is less sharp than the R wave in an ECG, and the spectral analyses related to the respiratory bands differ, however neither of these differences is statistically significant. In both the supine and head-tilt position PRV can be used in place of HRV. [68]

The PPG technology involves analysis of a pulse to pulse interval (PPI) to produce PRV, compared to the R to R interval (RRI) used to produce the HRV. Pulse wave analysis involves the anacrotic phase, the rising due to ventricular systole generating a pulse wave distally, and the catacrotic phase, the decline that corresponds to cardiac diastole. The anacrotic phase occurs shortly after the QRS complex appears on an ECG, which would be the delay adjusted for by the PTT. Any deviations from the RRI by the PPI could result from artifacts or a physiological variability in the PTT. Good agreement between HRV and PRV has been found for younger subjects during rest. Other studies have found PRV to overestimate HRV especially the HF domain measures. More research is needed to clarify the agreement on PRV in relation to HRV and to provide a consistent methodology for comparison. [72]

Changes in HRV are a non-invasive method to determine the balance between the sympathetic and parasympathetic nervous systems and can identify any cardiovascular abnormalities [2, 4]. Analysis of HRV data includes time domain and frequency domain measures, however the two methods cannot be used to make direct comparisons [1, 4]. Data has traditionally been collected in a laboratory using ECG and analyzed using software such as the Kubios HRV tool to filter and correct for any artifacts in the data [3, 4]. Advances to technology have led to the development of cell phone applications that can be used to collect and analyze HRV in a non-laboratory condition, assuming that the methods are valid [62, 64, 67]. Alternatives to traditional ECG data collection utilize the camera of a smartphone and photoplethymographic technology to detect PRV changes, which are comparable to HRV changes [62, 64, 67, 68, 72]. Athletes can use HRV analysis to determine the effects of training on the resting levels and during recovery and the use of smartphone technology can make this collection readily available without a laboratory setting [4, 62, 64, 67].

Heart Rate Variability with Exercise and Training

Athletes who undertake endurance training typically have lower resting HR and higher vagal tone [21]. Resting levels of anaerobic and aerobic trained athletes showed sinus bradycardia compared to healthy controls and sedentary controls of the same age [98, 99]. In addition, following exercise trained individuals have a quicker return to parasympathetic tone and a more pronounced sympathetic withdrawal [21, 100]. An increase in HRV, indicative of increased parasympathetic activity, would reflect adequate recovery as well as a positive adaptation to training and allow for an increase in training load [21, 47]. Vagal outflow may be diminished following heavy cardiovascular training loads, with this reduction being even longer for those with poorer cardiovascular fitness [101]. Because of the slow rate of metabolism of norepinephrine by the cardiac tissue, the withdrawal of sympathetic activity following exercise may be slowed by an increase in other accumulated stresses that may have lead to an increase in norepinephrine output [19, 46]. The intensity of exercise is a bigger predictor of diminished HRV post exercise and a slower return of parasympathetic activity than the duration of the exercise session [50]. Understanding the changes that occur in laboratory tests of HRV would then need to be brought to field testing to determine if HRV can be used to adjust training [47].

Compared to healthy non-athletes (n=50), both anaerobic (n=20) and aerobic (n=30) trained athletes had significantly lower resting HR and resting blood pressure (BP). There was no observed difference in HRV between the groups, however the RMSDD was higher in both the static and dynamic groups (P=0.06). Static athletes also presented with a tall R-wave, consistent with findings in previous research. While the control group consisted of healthy non-athletes, no information was given as to whether these subjects were active therefore comparison with the professional athletes may be misleading. [98]

Following exercise, HRV dynamics can be used to evaluate parasympathetic return and sympathetic withdrawal. The rate of vagal reactivation is dependent upon the type and intensity of exercise. As lower intensity exercise involves less sympathetic activation, recovery is assumed to be different than from high intensity exercise that involves a greater sympathetic response. The loss of central command and baroreflex activity following exercise combined with changes in cardiovascular function are believed to contribute to parasympathetic reactivation following exercise. However the increase in sympathetic activity of moderate and high intensity activity during exercise mean slower sympathetic withdrawal following exercise. Using short-term Fourier transformation, while HF power reflected slower changes following moderate and high intensity activity compared to quicker changes following low intensity exercise, TP, which reflects LF power as well, varied. Because LF reflects sympathetic changes as well as parasympathetic changes, the contributions of the sympathetic changes would be reflected in TP. While intensity of exercise influenced HRV, the length of distance of the exercise did not, meaning that the same exercise intensity sustained over a longer period of time does not significantly affect HRV levels. [50]

The recovery of HRV was evaluated within one hour, 24 and 48 hours following a single bout of either interval training or constant exercise to determine how moderately trained subjects (n=10) respond to routine training sessions. The interval exercise consisted of one minute periods of maximal intensity exercise followed by four minutes of submaximal base exercise repeated nine times for a total of 45 minutes while the constant exercise was of an adjusted duration to allow subjects to perform the same total work as in the interval exercise. Cardiac autonomic control prior to the exercise sessions was not significantly different. Within the first hour following the interval exercise there was a slower return to parasympathetic activity compared to the constant exercise as expressed by the higher total power values after cessation of exercise and high HF values during the 20 minute post exercise period ($P<0.05$). Lower mean R-R values at the end of the interval exercise compared to the constant exercise were reflected via a higher heart rate, continued parasympathetic withdrawal and sympathetic dominance. Because subjects underwent the same amount of work for both exercise sessions, the difference in ANS response could be related to the type and the intensity of work and not the total physical work performed. Recovery 24 and 48 hours after the exercise resulted in no significant differences between the groups for HRV values for either type of exercise, potentially indicating that the total power of the exercise may have more influence over recovery than the type of exercise. [102]

The time course of parasympathetic reactivation was examined in 15 moderately trained individuals following repeated sprint exercise, equivalent net energy expenditure of moderate and continuous exercise and equivalent anaerobic energy interval exercise. The HRR for 60 seconds following exercise as well as the SDNN, RMSSD, AR HF and HR for the five to ten minutes post-exercise were significantly lower in the repeated sprint and interval exercise sessions when compared to the moderate and continuous exercise ($P<0.001$). Compared to the moderate and continuous exercise of similar energy expenditure, repeated sprint exercise led to a significantly more delayed parasympathetic reactivation. This indicates that the factors associated with anaerobic contribution to exercise are more important than aerobic power or energy expenditure with parasympathetic reactivation. Increased anaerobic contributions, such as metabolites and the increased influence of central command during anaerobic exercise, were significantly related to all post exercise parasympathetic reactivation indices ($P<0.001$). Autonomic control of HR appears to be dependent upon the intensity of the exercise and not the duration or the amount of energy utilized. Heightened sympathetic activity, elevation in adrenergic factors and local metabolites accumulated during sprinting is similar to what is seen during strength training. [5]

The acute ANS recovery from three different training intensities was quantified via HRV and compared between highly trained endurance athletes (n=9) and recreationally trained subjects (n=8). Both groups performed a preliminary test to exhaustion to determine baseline characteristics and training levels. The highly trained subjects performed a four week training period by replacing one normal workout with a session at intensities below their first ventilatory threshold (one at 60 minutes and one at 120 minutes), at threshold (30 minutes) or above second ventilatory threshold (30 minutes of intervals). The highly trained group performed one session of intervals at the second ventilatory threshold. Prior to exercise HRV measurements were taken at rest and post-exercise HRV measurements were taken during a four hour session. The exercise below the first ventilatory threshold demonstrated little or no delay in return to parasympathetic tone regardless of length. For many athletes, this level represents the majority of their training, which means that recovery from activity at this intensity should prove to return the athlete to homeostasis prior to their next training session. When the intensity was moved to threshold, there was a significant delay in ANS recovery. The interval exercise above the second ventilatory threshold resulted in a significant delay in return to autonomic balance and was significantly lower when the recreationally trained group was compared to the highly trained athletes. There was no significant difference in the return to autonomic balance between sessions above the first ventilatory threshold indicating that once activity is above the lactate threshold there will be a delay in return to homeostasis during recovery. Athletes who fail to recover from exercise sessions of increased load may be at risk for overreaching or overtraining if adequate recovery were not introduced therefore the recovery would need to reflect intensity of the exercise. [48]

Exercise load is perceived to be a contributing factor to HRV. Healthy subjects were divided into groups based on the Baecke sport score, sedentary (n=12) who participate in less than two hours a week of activity, moderately trained (n=10) who participated in four to six hours a week of aerobic training and highly trained (n=9) who participated in over 18 hours a week of intensive aerobic training. All subjects suspended activity for two days prior to resting data collection. The moderately trained subjects had an increase in vagal related indices that was not seen in the sedentary or the highly trained subjects. Even rested and with the highly trained subjects having no indication of overtraining, lower HRV levels were found, reflecting the bell-shaped relationship between exercise load and HRV. The highly trained subjects did display a lower resting HR, most likely related to left ventricle remodeling and not the parasympathetic influence. Since these subjects were selected based on a quantitative training dose basis and were not under specific training loads monitored for intensity and duration, there is limited interpretation that can be made from this study. Although higher amounts of training seem to be related to reduced vagal indices, those conclusions cannot be made from this study. [103]

The changes in vagal-related indices were assessed for healthy male runners (n=14) over an eight week training period. The physical assessment utilized was maximal aerobic speed as it is thought to be a superior predictor of endurance performance than VO_2peak and also has a stronger link between changes in HRV indices. Prior to training resting HRV indices had large to very large correlations with maximal aerobic speed and 10km run time. Following training there was a moderate relationship between changes in LN RMSSD at rest and changes in maximal aerobic speed (P<0.01) as well as a very large relationship between LN RMSSD at rest and changes in 10km performance time (P<0.010). The very large relationship between vagal indices and the 10km performance suggest that cardiac autonomic activity may be a better predictor of aerobic endurance than aerobic power. Analysis of pre and post-training results showed a main training effect for HR at rest ($P<0.01$) and LN RMSSD at rest ($P=0.03$). Vagal-related indices showed a trend throughout the training intervention toward higher parasympathetic levels. There was also a large correlation between LN RMSSD at rest and LN RMSSD post-exercise ($P=0.05$, $r=0.61$). It is difficult to make comparisons between these measures and those of other studies because of differing methodologies such as exercise intensity and positioning of the subject during the HRV data collection. During the study time to HRR continued to decrease for the first three weeks as cardiovascular adaptations improved. It remained steady until data collection following the taper week when there was a further decrease. There was a strong interdependency of ANS functioning an aerobic performance among these subjects following an eight week training program. [104]

Long-term ECG recordings for male elite distance runners (n=16) taken over a 48 hour period compared to a control group of sedentary males (n=13) revealed a pronounced bradycardia associated with increased vagal tone. The higher time domain measures of RMSSD and pNN50, associated with parasympathetic influence, correspond to the increased bradycardia and may be an effect of the increased cardiovascular training of the elite runners. All recordings were taken in the subjects' normal surroundings and not in a laboratory setting, which may have had a positive influence on the HRV measures for all subjects. The AR frequency domain measures of HF and LF power were both higher in the runners compared to the controls with the differences more pronounced at night. Based on the recordings being over a 48 hour period, direct comparison to shorter laboratory sessions cannot be made. [22]

Endurance training leads to improvements in many cardiovascular and metabolic variables and may also lead to increases in heart rate variability at rest. Twenty-four physically active subjects were divided by gender into four age groups, 20 year-old males, 20 year-old females, 40 year-old males and 40 year-old females. Following a standardized 12-week training program there was a significant total group mean decrease in heart rate at rest and during submaximal exercise. The FFT total spectral power and HF power using increased at rest for both age groups, with subjects in the 20 year-old age group having a larger autonomic adjustment to training, and the 40 year-old females having the smallest. This supports the theory that training decreases sympathetic activity of the heart and increases parasympathetic activity allowing for an increased parasympathetic control at rest and contributing to resting bradycardia. [21]

A similar study of HRV changes at rest and during post-exercise recovery examined 12 healthy males undergoing a six week endurance training program. The endurance training group (n=7) underwent cycle endurance training for six weeks while the healthy control group (n=5) continued with their normal activities of daily living during that time. Each group underwent a VO_2max test prior to the intervention and then had periodic follow-up sessions involving resting HRV, submaximal cycle exercise protocol and post-exercise HRV. At rest the endurance trained group had a significant decrease in HR and increase in FFT HF power and SDNN, agreeing with previous research that enhanced vagal tone contributes to resting bradycardia and increased parasympathetic dominance in these athletes. As this study length may have been too short to determine physiological changes to the heart muscle, it was speculated that the changes in cardiac ANS modulation contributed to the decrease in resting HR. [23]

With the additional consideration of subject training load via the Baecke sport score along with VO_2max results, four groups of male participants of similar ages and body mass index scores were assessed for pre-exercise HRV indexes and post-exercise HRR. Vagal related indexes were significantly associated with VO_2max, regardless of training load as fit subjects (VO_2max > 55ml*kg^{-1}*min^{-1}) had the highest HRV indexes even if they expressed low levels of physical activity (mean Baecke sport score 3.6 ±0.3). Conversely, HRR was negatively correlated with training load but not associated with VO_2max as the unfit subjects (VO_2max < 50ml*kg^{-1}*min^{-1}) moderately trained subjects (mean Baecke sport score 8.9±0.7) had a significantly shorter recovery time than the fit low trained subjects. This suggests that training adaptations have a greater association with training load and a lesser association with cardiorespiratory fitness levels. It is, however, difficult to assume intensity of the training of the subjects from the Baecke sport score, as recovery time is not considered in the duration of self-reported activity. [105]

As there is a lack of information on the link between ANS modulation and weight training performance, male weightlifters (n=7) underwent HRV testing during a 72-hour recovery period after an acute strength training program following 10 days of detraining. The FFT frequency domain measures of VLF, LF and HF power as well as the LFnu measures were used in the natural logarithmic form. The weightlifting performance recovered along with a parasympathetic rebound defined by a plateau of the HF values between 48 and 72 hours post-exercise. This suggesting an increase in parasympathetic activity can mirror the degree of performance recovery after weightlifting. Physiologically, delay in parasympathetic activity after anaerobic exercise may be explained by the increased energy requirement to repair muscle damage. However this does not seem to be associated with an increase in sympathetic activity as seen in endurance exercise. [80]

Comparing resistance-trained (n=15) and aerobically-trained (n=14) athletes to sedentary subjects (n=18) of similar age, body mass index, percent body fat and VO_2peak, there was no significant difference in HRV at rest. While training load did not have any influence on HRV at rest, subjects in both the resistance and aerobic training groups did have a significantly greater heart rate recovery (HRR) at 60 seconds post-exercise and a shorter time constant of heart rate recovery. There was no significant difference in HRV following maximal exercise testing for any of the groups. It is believed that the reduction in HRV following maximal exercise or supramaximal protocols are a result of increased accumulation of metabolism by-products and the influence of the metabaroreflex in the post-exercise condition. Vagal reactivation was observed with an increase on RMSSD during the recovery period in the aerobically trained group but not in the resistance trained or sedentary group. [99]

Reduced HRV in older subjects may be an indication of increased mortality, however endurance exercise training has been shown to have a cardioprotective effect. The normal reduction in HRV that occurs with age may be partially offset with regular exercise. Endurance trained masters athletes experienced a reduced FFT HF component and an elevated heart rate during recovery from high intensity exercise. This suggested an increase in parasympathetic withdrawal during the autonomic control of post-exercise tachycardia. However, it was purported that this sustained elevation in post-exercise heart rate may be required to maintain arterial blood pressure because of a reduction in total peripheral resistance. As reduced variability may predispose the heart to arrhythmias, reduced variability following exercise in older subjects may indicate an elevated risk of abnormal cardiac events and may be a better indicator of mortality rate compared to resting HRV levels. [100]

In older untrained men (n=93; age=55.6±7.4)), the effects of combined endurance and strength training were compared with endurance or strength training alone on HR dynamics at rest and during exercise. The AR analysis of the frequency domain variables HF power and LF power were used as HRV outcome measures. Those in the endurance group (n=23) and strength group (n=25) worked out two times per week while those in the combined group (n=29) worked out four times per week using the same protocols as the strength and endurance groups. The combined strength and endurance training enhanced the positive effects of endurance training on HR dynamics while strength training only led to minor insignificant changes to HR dynamics at rest. The non-significant results of the strength group should be interpreted with caution as males over 40 years old show less improvement than those 20 years old. [85]

Changes in HRV for 48 hours following an endurance cross-country skiing race were compared to pre-event levels collected 24 hours prior to the race. The ten healthy male subjects that participated underwent regular aerobic training prior to the study, however this training did not follow a specific protocol. For several hours following the exercise, vagal outflow was reduced yet rebounded on the second day after. Those with better cardiorespiratory fitness, per pre-exercise VO_{2max} testing, had a more rapid recovery. Changes in cardiovascular autonomic function following maximal exercise reflect the altered cardiac changes needed after exercise. Sympathetic dominance is needed to maintain adequate blood flow with reduced cardiac performance. As the body is able to return to its pre-exercise state, sympathetic withdrawal begins and vagal tone returns to pre-exercise levels. The rebound effect on the second day may be a reflection of increased sympathetic activity in anticipation of the upcoming race, however this has not been verified. [101]

The delayed post-exercise effect on HRV may differ with exercise of different intensities. Heart rate variability of 16 healthy experienced runners (n=2 female and n=14 male) was assessed via repeated measures ANOVA at one hour prior to and then one hour, 24 hours, 48 hours and 72 hours following moderate and severe intensity aerobic exercise sessions. The severe exercise sessions showed an increase in sympathetic activity and a decrease in parasympathetic activity at one hour post exercise, however the changes were reversed by 24 hours and remained constant for 48 and 72 hours post exercise for the pre-exercise level. Also present following the severe exercise session was a reduction in systolic BP. This reduction in BP may have been lead to the compensatory increase in sympathetic influence and decrease in parasympathetic influence immediately following exercise, which was reversed by the 24 hour data collection session. The moderate aerobic exercise sessions however resulted in no change in the ANS activity of the heart at any of the post-exercise times. [106]

The majority of post-exercise HRV studies focus on the cardiovascular response to endurance exercise which is different from the cardiovascular response to resistance exercise. Resistance exercise exerts an intermittent pressor response on the cardiovascular system rather than the volume load that endurance exercise exerts however little is known about the recovery of the ANS following endurance exercise. Autonomic recovery was not fully regained 30 minutes after either acute endurance or resistance exercise. While AR HF power was reduced, LF power was increased and the LF/HF ratio increased in similar fashion following both exercise bouts suggesting a shift toward sympathetic dominance, the greatest reduction in total power was seen after the resistance exercise. This suggests a greater reduction in parasympathetic modulation following resistance exercise. [79]

Pre and post-season evaluations were used to assess elite athletes for changes in strength and aerobic power as well as quantitative and qualitative changes in HRV measures. Resting heart rate and AR LF power (in m/s^2) in these subjects were significantly lower following seven months of training. Total and HF powers were not significantly changed however those subjects with increased VO_{2max} following the training presented with higher HF (m/s^2 and normalized) and total power compared to those with reduced VO_{2max}. Strength measures showed an increased in torque and a reduction in contraction velocity. Changes in muscle performance were related to changes in LF power. While the results of this study support the theory that those who are trained have higher parasympathetic activity it is possible that higher parasympathetic activity is the cause of improved fitness rather than the result. [107]

Resting HRV changes were examined in cross-country skiers (n=8 male, n=9 female) before and after seven months of competitive training. Monthly subjective reports of training load were also recorded. There were no significant differences between tests when separated by gender group, however as an entire group the total variability was significantly higher after the training period than before, possibly indicating an increase in parasympathetic modulation of HR. There was a non-significant effect for the increase in AR HF power, typically a better indication of parasympathetic activity, and the LF power taken in an upright tilted position was significantly lower, which could be explained by the combined gender group or could represent overtraining in some of the athletes. Only taking pre and post season HRV measurements, and not examining HRV during the season may have complicated this. There was a significant between-subject effect for gender on HF and total variability with females showing higher levels than males, indicating that some measures at rest may be influenced by gender. The influence of training load on HRV was not examined in this study and therefore makes no conclusions about the influence of training load on the post-season results. [108]

It was hypothesized that there would be a weakened relationship between R-R interval length and vagally mediated R-R interval variability in endurance athletes with OTS, indicative of abnormal cardiac autonomic function. This study included male (n=4) and female (n=5) endurance athletes who had been diagnosed with OTS and male (n=5) and female (n=5) endurance athletes to serve as controls. The study protocol included a 24-hour ECG monitoring during which a maximal exercise stress test and other clinical assessments (not presented in this study) were examined. Following six months of recovery for the OTS subjects and six months of no intervention for the controls the study protocol was repeated. Baseline measures showed differences in performance measures and maximal HR between the groups but no differences in mean HR and R-R interval variability. A moderate effect size for OTS (ES=1.01) on AR LF/HF ratio was found. Within subjects quadratic R^2 between HR power and R-R interval was significantly higher in the OTS group (*P*=0.034) at baseline and there was a large but non-significant decrease at the follow-up (*P*=0.11; ES=1.44). The relationship between R-R interval and vagally mediated R-R interval variability was stronger in OTS athletes, normalizing after recovery. This was different than expected, however the hypothesis was based on vagal modulation studies done with cardiac patients, not healthy subjects. Because this study involved a 24 hour ECG recording with maximal testing, the comparison to other studies is difficult. [27]

The specificity of training, endurance training versus power or anaerobic training, should elicit differing adaptations in muscle mass and in cardiac remodeling. Therefore it was hypothesized that elite track and field athletes would have differing resting HRV measures. Prior to the 2004 Olympic track and filed trials, 145 male and female athletes participated in resting HRV data collections. While it was hypothesized that the aerobically trained individuals would have significantly elevated levels of parasympathetic tone compared to the anaerobically trained group, a 2-factor analysis of variance (ANOVA) failed to show any significant higher level of interactions. The only significant differences were found between gender (n=58 females, n=87 males), indicating either differing adaptations for the genders or inherent differences in HRV. Because no information was included about training regiments, no conclusions about training intensity for either gender can be made. It is also possible that the elite level of the subjects made for similar resting HRV levels regardless of the type of training. Another potential limitation of the study is that data were collected prior to a national event and therefore emotional stress or the decrease in HRV associated with taper may have been factors. [57]

In order to remove the potential bias of precompetitive anxiety, 20 elite male track and field athletes participated in resting HRV data collections during the initial phase of periodization for the 2012 London Olympics. Athletes were divided into speed and power athletes (n=10) and endurance athletes (n=10). Endurance athletes had a lower resting HR than the power athletes, however the RMSSD lacked significant difference and the effect size was low. There were no significant differences in any of the frequency domain variables. Saturation of the parasympathetic nervous system, where the increase in acetylcholine saturates the sinoatrial node, is one explanation for the increase in R-R intervals without the associated increase in vagal activity that would be expected. Symbol analysis of the data, used to detect nonreciprocal autonomic changes, such as a decreased vagal modulation and increased sympathetic modulation not corresponding, did show differences between the two groups. If saturation is present, the increase in parasympathetic activity may not correspond with a decrease in sympathetic activity. Data were only collected at once session during the pre-competitive period, which did not allow for changes and adjustments in HRV that may occur during different times of the training cycle. [18]

Non-elite recreational male long-distance runners (n=8) underwent four assessments at eight week intervals prior to participation in the 2008 Roma Marathon. Subjects underwent pre-training testing to determine their individual training load as established by a modified training impulse ($TRIMP_i$) method. Both volume and intensity of training was determined for each subject individually based on their own physiological systems. The ANS adaptations to training shifted from vagal to sympathetic as the subjects approached the maximum training as assessed via and increase in the AR LF, BP and the AR LF/HF ratio and a decrease in AR HF, consistent with sympathetic activation. A curvilinear dose-response relationship between training load and ANS parameters was present. An increase in the LF component at peak training was able to predict individual athletic achievement. Direct comparison to other studies cannot be made based on these results as other training studies do not develop individual training plans which control for the physiological adaptations of the subjects. In addition, this study used highly trained subjects ($VO_2max=51.3\pm0.8$ $ml*kg^{-1}*min^{-1}$) who had a lifelong history of exercise. These results may not be transferable to sedentary subjects, female subjects or subjects involved in different types of training programs. [109]

The majority of studies focus on subjects involved in individual sports such as running, swimming and cycling that may not be comparable to those competing in team sports where activity is not always continuous. In order to examine the effects of training on physical performance, cardiovascular variables of exercise HR, HRR and post-exercise HRV were monitored in 92 highly trained young soccer players over an entire competitive season. Data were collected prior to the season, at the mid point and at the end of the season. It was hypothesized that a substantial decrease in HR during submaximal exercise and/or and increasing HRR and vagal related HRV indices would indicate improvements in cardiorespiratory and neuromuscular fitness-related performance variables. A within-player decrease in exercise HR and/or an increase in LN RMSSD, both improved vagal-related changes, were associated with improvements in maximal running velocity during an incremental running test. Baseline levels of submaximal exercise HR were moderately-to-largely correlated to improvements in maximal running velocity over the season. It can potentially be inferred that those who start with greater initial parasympathetic tone, as indicated by a faster HRR, can show the greatest improvements, however further research is warranted. Previous research has found a possible link to increased parasympathetic activity and the increased capacity to adapt to higher training loads. Baseline HRR and LN RMSSD were moderately correlated to changes in maximal sprinting speed and performance in repeated springs. Also, baseline LN RMSSD was moderately correlated to changes in acceleration. It is possible that the HRV measures were affected by acute fatigue, hydration, stress or the exercise load placed upon the athlete in testing. None of these factors were controlled for in the study therefore it is possible that some of the athletes were in a state of overreaching or overtraining at the time of the data collection. [110]

A prospective longitudinal design was used to determine the possibility of using HRV parameters during training to predict non-functional overreaching in female wrestlers (n=34). Based on meaningful results from a pilot study, HRV measures were taken no later than six weeks preceding international wrestling competitions to obtain valuable markers and reference thresholds of HRV parameters. Weekly HRV measures were taken using the OmegaWave sport technology system on Sunday evenings following a day of full recovery. Time domain variables of SDNN and RMSSD and frequency domain parameters of TP, LF, HF and LF/HF were analyzed. Weekly training load was described as either high, medium or low based on the number and intensity of the training sessions. Those characterized as having non-functional overreaching had associated HRV changes for three or more weeks with a concurrent decrease in physical performance. Athletes who were in a state of overreaching had fluctuations in HRV parameters during recovery however that response was either an increase (n=32 measurements) or a decrease (n=29 measurements) in HRV compared to the normal response (n=216 measurements). As there are two types of OTS, involving both sympathetic and parasympathetic changes, subjects fitting either change were considered to be at risk. A Pairwise comparison for time domain indices was significant ($p < 0.0001$), however TP, HF, LF and VLF were significant only between increased and normal responders ($p < 0.0001$). The LF/HF ratio was significant between decreased and normal responders (p=0.002) but not between increased and normal responders (p=0.662). The non-invasive method of HRV makes it an easily obtainable early warning sign for OTS, which could then be followed with blood work or other invasive tests if symptoms persist. One limitation of this study is that by taking only weekly measurements following the recovery day there was no indication of lack of recovery during the week or way to calculate normal daily fluctuations. [111]

Elite male soccer players (n=8) underwent nighttime HRV analysis and ultra-short-term HRR analysis during weekly small-sided games in practice in order to examine the relationship among these autonomic indices during eight weeks of preseason training. The workload of the small-sided games was tacked via GPS monitoring. The HRR was determined via HR monitors with HRR defined as any sudden and consistent decrease in HR over a predetermined period of time of ≥ 20s following a peak of ~85% of predicted maximum HR. In those with no difference in workload from week one to week eight (n=6), HRR parameters were not significantly different among the slope of the regression line at five, ten, fifteen and twenty seconds of recovery but when expressed as a percentage of peak HR, the difference was significant from three seconds onward. For nightly HRV analysis the players wore HR monitors to assess the mean of four daily, continuous three hour night-time recordings with the days randomly selected for each player. The changes in HRV from week one to week eight were significant for SDNN and SD of the long-term continuous RR variability and not the short term SD or RMSSD. The coefficient of variation (CV) of the RMSSD over the preseason was found despite no evident changes in RMSSD. It is possible that the training design of the preseason, which was intended to induce supracompensatory changes, may have affected the CVRMSSD. A continuation of the data collection during the season may produce different changes. As the data were collected overnight for four days out of the week, it is difficult to compare these to single weekly data collections or morning data collections as are found in other research studies. [112]

In a review of the literature the value of assessing cardiac parasympathetic reactivation following exercise was examined in order to make recommendations for training. Exercise intensity influences acute recovery and for up to 90 minutes post activity parasympathetic activity does not return to pre-exercise values. The lower intensity exercise shows the quickest return and high intensity exercise shows the slowest. Intermediate recovery for low intensity exercise can be seen at 24 hours however threshold and high intensity exercise can take up to 48 hours or more. These effects are dependent upon the fitness level of the individual as highly trained individuals recover the quickest. When strength training was examined, there were differing results indicating that more research is needed for resistance based exercise and cardiac parasympathetic activity monitoring. It is noted that individual difference are paramount and therefore age, gender, fitness level and type of training must be taken into consideration. It was recommended to use daily measures taken upon wakening using the RMSSD measure and training logs to determine level of intensity, sleep quality, stress, fatigue, soreness and duration of exercise as all of these factors have been deemed necessary to evaluate recovery.[75]

In athletes, HRV is often used to determine recovery from exercise, adaptations to training load and fatigue; all possible concerns for overtraining [5, 104, 110]. Having a standard protocol and established norms would allow for athletes to utilize an HRV protocol without requiring each athlete to establish their own baseline values [1, 28]. The majority of HRV analysis focuses studies have focused on endurance athletes, however direct comparisons cannot be made with athletes who undergo interval or anaerobic training [23, 79, 99]. Endurance athletes will often train at levels below anaerobic threshold allowing for a faster recovery compared to training that is done at a higher intensity [48, 50]. With interval training immediate recovery may be delayed because of increased sympathetic activity and parasympathetic withdrawal necessary to maintain blood flow whereas the continuous training at one intensity may result in just parasympathetic withdrawal and not an increase in sympathetic activity [5, 99, 102, 106]. The ANS response is different with acute sessions of anaerobic compared to aerobic training therefore it can be presumed that the HRV norms for athletes will reflect their dominant training [18, 79, 107]. In elite athletes, however the difference in HRV levels between aerobic and anaerobic athletes has not proved to be significant, although at that level the differences may be so small that significance cannot be detected [18, 57]. Additional considerations should also be made for athletes in team sports as very little research has been done on these subjects [110]. It is important to consider the athlete's sport and training type, intensity and fitness level along with other factors such as age and gender when evaluating recovery [27, 49]. Because there are normal fluctuations of HRV, utilizing data obtained during differing intervals of training may provide differing results and therefore the current trend is to look at multiple consecutive days of HRV data [70, 110-112].

Daily HRV measurements

Daily HRV measures have been used to determine the effects of normal and overtraining on competitive athletes as well as to assess the potential for injury risk [6, 65, 66, 70, 113].

Using daily measures of HRV as well as information about the previous day's training load or type of training and the subjective RPE from the athlete can give an accurate description as to how the athlete is tolerating the activity [6, 49, 66, 113]. Analysis of the daily HRV seems to indicate that the daily change is most relevant when compared to the average of the previous five to seven days rather than compared to the change of just the previous day [6, 47, 70]. Using HRV to guide training can give a better indication of recovery and how well the athlete is tolerating the imposed training load [6, 47]. When compared to traditional training, HRV training resulted in improved endurance performance [114].

Two elite triathletes (n=1 male, n-1 female) underwent longitudinal HRV monitoring over a 25 week high volume training period prior to a key event and as a result a potential new way of using HRV to monitor stress and recovery was presented. The athletes used a training journal to record the duration of daily training, psychometric questionnaire to record daily levels of sleep quality, muscle soreness, stress and fatigue on a Likert scale, and HRV analysis using a heart rate monitor. The RMSSD was chosen as the HRV measure, which was then log-transformed with the LNRMSSD plotted as a function of the corresponding mean R-R interval value on the same day. Differences were considered on an isolated day (day seven of each week), on a rolling seven day average, the total of a one week period (Monday to Sunday) and a seven day rolling coefficient of variation (CV). The SWC was calculated from individual CV in LNRMSSD, RHR, training volume and psychometric indices data over the first to weeks of recording. A change of more or less than 0.5 of the CV was considered the SWC. The magnitude of change between weeks was expressed as standardized mean differences or effect size and linear regression was used to examine the rate of change in RHR, RMSSD as well as selected psychometric indices. The female athlete developed non-functional overreaching

(NFOR) around day 37 however she continued to train and attempted to compete but did not finish the event and subsequently diagnosed with the herpes zoster virus, which can be linked to immunosuppression and chronic fatigue in younger individuals. The male athlete finished third with a personal best result. Daily and rolling values for RHR gradually increased while LNRMSSD gradually increased for the NFOR athlete while for the control athlete the values decreased and increased respectively. The results of the competition supported the notion that the female athlete was at risk for OTS while the male (control) athlete was effectively prepared for competition. For these athletes the HRV measures were more indicative of change than the psychometric indices. Isolated daily HRV values were meaningless as 63% for the control and 100% for the NFOR athlete fell outside of the SWC, as determined by the CV, and weekly or rolling averages are more meaningful. The weekly LNRMSSD fell outside of the SWC for both the control and NFOR athlete however these were deemed to be a normal part of the training cycle. Further investigation into the appropriate use of HRV and appropriate statistical measures for determining SWC are warranted. [70]

A prospective study was initiated to test the usefulness of daily HRV measurements to dictate individual endurance training where the training was decreased when the HRV decreased and increased when HRV remained the same or increased. Healthy male recreational runners (n=30) were placed into one of three training groups, predefined training, HRV-guided training and control. The HRV group used the following reference value to determine training level: SD of the 10-day AR HF power average was subtracted from a rolling 10-day average of HF power. Any daily value lower than one SD below the mean resulted in a decrease in training while any change within one SD or greater resulted in high-intensity training with a maximum of two high-intensity days in a row. Fitness improved with the HRV based training and endurance response was better than that in the pre-determined training group even with less high-intensity training days. [114]

The effectiveness of aerobic training guided by HRV was assessed and compared between healthy, moderately active men (n=24) and women (n=36). The participants divided into three groups, standard training, HRV training and control with an additional HRV group of women undergoing specialized training tailored for women. The reference value was based on a rolling10-day window of RR intervals with a fairly complicated formula of calculating SD measures with SD1 defined as a decreased if the daily value was lower than SD subtracted from the mean. Training was decreased if the change was greater than SD1. The female only HRV group only participated in vigorous intensity exercise if the daily mean was above the rolling mean and greater than the previous day. The HRV-based exercise was beneficial for men but did not have the same response in the moderately active women. The female specific training resulted in fewer vigorous exercise days and the results of this different training were inconclusive, as the women seemed to require a longer period of time to recover from vigorous exercise. As these were moderately training participants no conclusions can be made about elite athletes who undergo similar training. [84]

Changes in daily HRV parameters were used to differentiate between athletes in a protocol to induce functional overreaching (n=16) and controls (n=8), to determine if daily or weekly HRV changes would delineate change associated with overreaching and if the changes in ANS would be associated with cardiovascular changes in maximal and submaximal exercise. Training was monitored for seven weeks during the competitive triathlon season with the intervention group undergoing an increase in activity by 40% during weeks five, six and seven following a taper in week four. All subjects measured morning HRV using HR monitors with the last four minutes of eight minutes recorded in the supine position and seven minutes recorded in the standing position used for analysis. The parasympathetic modulations of RMSSD and the Goertz algorithm was used for the frequency domain measures of HF and the sympathetic modulation of LF/HF were used as outcome measures with both once a week and weekly averages considered. Half of the CV was considered for the SWC. Thirteen of the subjects in the experimental group had decreased running performance compared to pre-training values and a high level of perceived fatigue following the overload period followed by a supracompensatory increase in performance following the taper. The differences in groups using the single day values for HRV taken in the supine position were unclear while the weekly average values of HRV parameters demonstrated a greater increase in LNRMSSD in the experimental group when compared to the controls. Similar trends were seen in the HF and LF/HF in the supine position. In the standing position the single day value differences in LNRMSSD and LF/HF were unclear but were likely to almost certainly greater using the weekly averages for LNRMSSD and log HF. The use of mean weekly values was found to be superior than isolated HRV values in assessing training induced adaptations and that day to day fluctuations make HRV analysis of single day values insensitive to clearly determine changes associated with functional overreaching. In these athletes resting HR decreased in the experimental group during the overload stage yet remained constant in the control group. This linked the experimental group to an increase in parasympathetic activity during that time that when paired with the parasympathetic hyperactivity demonstrated by the HRV may reflect a supracompensatory saturation of the sinoatrial node.[6]

Daily changes in ultra-short HRV measures taken via smartphone application were assessed from two weeks of varying training loads during off-season training for collegiate female soccer players (n=10). Additionally, an association between daily HRV fluctuations and additional markers of training status were used to facilitate meaningful interpretation. Measures were taken every morning in the supine position. Per previous research, one minute of measurement was taken following a one minute stabilization period. Data was then exported to the from the smartphone application to the researchers. Questionnaires using a five point Likert scale assessing perceived sleep quality, muscle soreness, mood fatigue and stress were completed three days a week and training load was calculated as the ratings of perceived exertion (RPE) of the training session multiplied by the training duration for conditioning sessions and RPE multiplied by repetitions performed for the strength training sessions. All daily values of LNRMSSD were compared to the baseline, established as the first day of data collection, which followed 72 hours of rest, with the effect size serving as the threshold of change. When the confidence limit crossed the threshold of .02, positively or negatively, the effect was unclear. The SWC was evaluated as half of the CV as determined by Plews [70]. Correlation coefficients were determined between the coefficient of variance of the LNRMSSD and the fitness and individual averaged psychometric variables. The effect of the greater training load in week one lead to greater reductions in LNRMSSD from baseline compared to week two with lower reductions found in those with a higher level of fitness and lower perceived fatigue. However since the change was only assessed versus the presumed baseline of day one and did not account for any accumulated change of HRV. In addition, there was a decreasing trend for 48 hours following more intense days. Results suggested an individual response was more accurate than a group change and confirmed the need for individual analysis of change. It is plausible that the shortened recording period and the questionable ability of the smartphone algorithm to correct for irregular heartbeats may have been problematic. [66]

In a case study of a collegiate male cross-country athlete, the association between eight kilometer race performance and the smartphone derived HR and LNRMSSD was evaluated during one competitive season. Training load was calculated by multiplying the training session in minutes by the RPE, training impulse was calculated by multiplying the average HR of each session by the duration in minutes and daily wellness was calculated by psychometric data recorded on a Likert scale for perceived levels of fatigue, sleep quality, muscle soreness, stress level and mood. Morning HRV measurements were taken via the ithlete™ smartphone application with no less than five recordings taken per week. Breath rate was standardized to 7.5 breaths*min^{-1} and each test consisted of a stable 55 second reading. The mean and CV (calculated as (weekly SD/ weekly mean) X 100) for the HR and LNRMSSD*20 measures were determined each week. The race time was taken from official race results provided by the host University. There was a strong relationship between race time and the CV of weekly HR (r=0.86) and LNRMSSD (r=0.92) and a moderate relationship between mean HR (r=0.63) and LNRMSSD (r=0.60). While research supports weekly values over daily values, this case study indicates that the level of variability may be a better indicator than mean values alone. This supports the idea that daily fluctuations are normal and may therefore be lost when only mean values are examined.[71]

Over a 10 week period the training load and psychological stats of elite male gymnasts (n=6) was evaluated using HRV, RPE of the previous day's training and Foster's psychological complaint questionnaire. Morning HRV monitoring predicted the RPE of the previous day session with significant correlations for the Δmean RR, Δmean RR and ΔLF% ($p<0.001$). The Foster's index score showed a trend toward correlations and a significant relationship with ΔHF%. With no increase in FFT LF or decrease in HF band over time and no changes in the performance tests (1 repetition max on bench press, standing balance, squat jump, countermovement jump and agility *T* test), it was assumed that the subjects were not overtrained during this time. In this study HRV accurately reflected training load and psychophysiological status of young elite male gymnasts and is an objective way to monitor the training load in order to reduce the risk of overtraining. [49]

Ten national level athletes utilized a practical application of daily HRV data to adjust training load based on vagal activity. A reduction in vagal activity resulted in a decrease in training load in an effort to enhance recovery while a high vagal activity allowed for an increase in training intensity. Daily HRV data was analyzed using an algorithm based on a minimum of the previous five ANS assessments and a maximum of the previous 20 ANS assessments based on daily home-based ECG recordings. Those athletes with high vagal activity in this study had an increase in change in performance, defined as a difference between the best sport result in the prior six weeks of the HRV-adjusting period and the best result from the previous season, expressed as a percentage of change. The high vagal activity was presumed to enhance the quality of training, increase readiness and be a positive influence on performance. Conversely, low vagal activity was associated with deterioration in performance and those subjects were assumed to be training above their actual training capacity, potentially putting them at risk for overtraining. All alterations were made on an individual basis and potentially cannot be duplicated for other athletes. In addition, the absence of matched controls and the small number of participants are limitations in this study. [47]

An observational study was done to investigate the changes in the HRV of professional baseball starting pitchers over a five-day pitching rotation schedule and to examine individual differences in resting HRV measures between pitchers. It was hypothesized that the day following a scheduled pitching start (referenced as Day 2) the resting HRV levels would decrease showing signs of increased sympathetic activity and that if resting levels did not increase prior to a start (Day 1) the individual would not be fully recovered and might be at risk for an overuse musculoskeletal injury. Eight males competing at the Single-A level participated in almost five months of daily resting supine data collection upon their arrival to the team facility prior to any activity. The time of day of data collection varied due to other team, travel and personal commitments of the participants. Data were collected for 10 minutes with the log transformation of the RMSSD of the middle five minutes being used for analysis. Participants who suffered an injury, were removed from the starting rotation or released from the team ceased data collection at that time therefore not all participants had the same number of data points. A split-plot repeated measures ANOVA was used to examine the influence of pitching rotation day on resting lnRMSSD. The resting lnRMSSD on Day 2 was significantly lower than all other rotation days ($p \leq 0.05$) but returned to baseline value by Day 3 of the rotation schedule. As starting pitching has previously been identified as a highly intense physiological task, the alteration in HRV is believed to be a response to the intensity of the previous day's workload which was then resolved within 48 hours. Had the lnRMSSD remained lower beyond Day 2, the subjects may have been at risk for OTS or musculoskeletal injury. This also supports the notion that daily measures are needed to best reflect change as the athletes were under a five day pitching rotation and not a seven day work week. There was no significant interaction effect between rotation day and pitcher, supporting the need for evaluating and interpreting data individually. Limitations in this study include the inability to alter training load as well as the inability to control for the time of the daily data collection and collection may not have occurred for each subject every day. With the ability of subjects to monitor HRV on their own, the daily data collection may have been improved. [113]

With the increase in the use of smartphone technology, daily HRV monitoring can effectively be done outside of the laboratory environment [62, 66]. The use of training load, based on the type of training as well as the subjective information from the athlete as to how well the tolerated the training, along with the objective HRV data the coach and athlete can easily adapt training in order to foster an environment that can help prevent OTS and potentially injury [6, 49, 70, 113]. Just as adaptations to training are individual, changes in HRV are individual in nature therefore each athlete must be compared to his or her own values in order to determine if the change in HRV is clinically significant [47, 66]. The most appropriate method for determining clinically significant change in HRV has been based on either 0.5 SD or 0.05 CV, however there has been no research to justify the use of these values [8, 70, 78].

Heart Rate Variability, Heart Rate Recovery, Blood Pressure and Cardiovascular Risks

Heart rate variability, BP and HRR can both be influenced by the autonomic nervous system [77, 115]. Autonomic dysfunction, characterized by sympathetic dominance is associated with cardiovascular disease and is related to poor aerobic fitness and body composition while higher heart rate variability has a cardioprotective effect [1, 36, 37]. Regular physical activity may protect against arrhythmias by increasing vagal tone both at rest and after activity, with females maintaining a higher vagal tone than males with comparable training volumes [116]. Trained individuals also have a faster HRR compared to untrained subjects and this quicker return to normal vagal activity may be a cardioprotective effect to prevent excessive cardiac workload [117]. However sudden death due to cardiac abnormalities may occur in young competitive athletes as well as older populations competing in endurance events [118].

While HRV and HRR are both used to assess autonomic function post-exercise, the relationship between the two has not been verified. Research often assesses HRR in the standing position and HRV in the seated or supine position therefore a relationship must be established in order to determine if direct comparison can be made as position influences autonomic function. Physically active males (n=31) underwent one data collection session consisting of resting HRV data collection in the supine and standing positions prior to maximal exercise testing. Standing HRR was calculated in absolute and relative terms as the HR decrement from the HR peak obtained during exercise to the HR at minutes one, three and five of active post-exercise recovery and normalized by the initial HR prior to exercise. An increase in parasympathetic withdrawal and sympathetic enhancement was observed between the supine and seated HRV measurements. There was a positive correlation of normalized HRR with indices of combined sympathetic and parasympathetic activity of the AR frequency domain HRV measures LF, LFn and LF/HF ratio, for the third and fifth minutes in the supine position and the fifth minute in the standing position. For measures related to parasympathetic activity, pNN50, RMSSD, HF and HFnu, were negatively correlated in the standing position with HRR in the third and fifth minute. Therefore though it is accepted in the literature that the first minute following exercise might not be the most appropriate post-exercise time for clinical evaluation of HRR in healthy males. It was concluded that HRR is better evaluated with initial HR and peak HR during exercise than resting HRV levels, regardless of positioning. [119]

There was no association found between resting HRV and HRR following a maximal graded exercise test in healthy college aged males. The subjects in this study however, were not highly trained with a mean VO_{2max} of 46.39 $ml*kg^{-1}*min^{-1}$. No information was given about the training done by these subjects, only that they were classified as healthy and had no signs of cardiovascular disease. Significant inverse correlations were found with SDNN and maximum heart rate and heart rate recovery one and two minutes post-exercise. Because previous research has determined that higher aerobic fitness levels are associated with greater HRV and HRR, it is possible that these subjects did demonstrate a great enough fitness level for improved HRR. Also, those with greater cardiovascular-parasympathetic tone at rest have a lower maximal heart rate and a greater drop in HRR. Similar research with highly trained individuals may result in different outcomes. [115]

Endurance trained athletes with a VO_2max above the 99th percentile participated in two data collection sessions, one maximal graded exercise test and one resting HRV data collection session. The autonomic activity of the 19 subjects (n=8 male and n=11 female) was assessed via resting HRV and HRR post VO_2max testing. The resting HRV of the subjects is poorly correlated with aerobic fitness and volume of physical activity for all subjects, but HRR is strongly associated. These findings were attributed to the resting HRV being determined by phasic changes in vagal efferent activity and HRR reflecting cholinergic signaling in the SA node. This is consistent with the findings of other studies that also found a lack of relationship with VO_2max and HRV and between HRV and HRR. The strong relationship with HRR following a maximal exercise test with VO_2max (r=0.62) and physical activity (r=0.55) are also consistent with previous literature. Body composition in this group was assessed via body fat (underwater weighing), BMI and waist circumference. Previous research has demonstrated a significant relationship between body composition and ANS, with improved ANS in those in a healthy body composition range. This group had relatively low levels of body fat and a poor relationship between body composition and autonomic control via both HRV and HRR. [120]

Autonomic modulation has also been related to body composition. Poor HRR and HRV have been previously associated with increased body mass index (BMI), larger waist circumference and higher body fat percentage and improvement in HRR and HRV has been found after weight loss interventions and endurance training programs. A significant negative correlation was found with sum of skinfold and HRR one and two minutes post-exercise while a significant positive correlation was found between VO_{2max} and HRR two minutes post-exercise. This indicates that cardiovascular fitness relates to a faster HRR while increased sum of skinfolds relates to a slower HRR following maximal exercise. Typically, those who are aerobically trained have a healthier body composition compared to sedentary populations and the addition of aerobic exercise with weight loss has to potential to improve autonomic function in those at risk for metabolic syndromes. While this can give insight to those with risk factors for cardiovascular disease, it does not offer any insight for a trained population. [37]

The effect of sum of skinfold measurement on HRV following maximal exercise was further investigated on healthy male subjects. Following data collection, the subjects were then divided into groups based on their sum of skinfolds, either above or below the mean. The two groups had no significant differences in age, height or VO_{2max}. Based on the results, it was suggested that greater sum of skinfolds was related to delayed return of HRV toward baseline following exercise, which indicates either a delay in sympathetic withdrawal or parasympathetic dominance. Because VO_{2max} and post-exercise HRV had no association, it is possible that endurance training may result in minimal post-exercise HRV changes and body composition may be a more predictive factor. However the subjects in this study were not highly trained or endurance trained individuals making cross-comparison with trained individuals difficult. [36]

Trained, but not elite, distance runners over the age of 30 underwent 24 hour Holter monitor HRV analysis. During that time period females displayed a higher minimum heart rate. However males displayed higher FFT frequency domain measures of total power and LF power in m/s^2. The higher TP in males was attributed to lower minimum heart rate and higher end diastolic volumes. There was no gender difference for HF power in m/s^2, however in normalized units (n/u), females had higher HF values and lower LF values. Those with higher training hours, both male and female, displayed lower LF power and higher HF power, however for females this occurred during the nighttime while for males this was during the daytime. With similar training values females had increased vagal tone, which may offer protection against exercise induced ventricular arrhythmias and contribute to a lower risk of sports-related sudden cardiac death. [116]

Male (n=16) and female (n=19) elite cross-country skiers monitored HRV on a weekly basis over a one year training cycle. All measurements were taken first thing in the morning on a day that followed a low-intensity training day. Additionally, RPE for every training session was multiplied by the duration to determine training load, which used to calculate the average weekly training load. For each training period, the average weekly training load data and weekly HRV data were averaged. At this elite level there was no gender difference in HRV at rest. It was speculated that the athletes had reached saturation of the vagal receptors, as there was no difference in HRV markers during any of the training periods, despite increases in training load. Mean R-R measures, which have the smallest individual variance, did show a significant ($p<0.05$) difference between training sessions, but not between genders. A limitation could be the use of one weekly data collection of HRV compared with a weekly average of training load. This could mask the ANS changes. Weekly measures taken in the standing position, which followed the supine position and presented an orthostatic challenge, showed higher markers of sympathetic activation in the males, perhaps indicating that the females do have a cardioprotective effect. [76]

Cardioprotective effects are not exclusive to endurance-trained athletes. Strength and endurance trained athletes had higher left ventricular internal dimensions and left ventricular wall thickness compared to healthy, untrained controls. As expected in regards to adaptation to their specific training, strength-trained athletes had a thicker left ventricular wall than endurance-trained athletes while the endurance–trained athletes has a larger internal dimensions than the strength-trained athletes. Following exercise, both groups had a faster heart rate recovery compared to the controls, with no significant difference between the strength and endurance-trained groups. From this information, it can be presumed that vagal adaptations to exercise are independent of morphological changes, however the effects of exercise on central command and baroreceptor resetting following exercise is unknown. One limitation to this study is that recovery was examined only following aerobic exercise. The effect of HRR from strength exercise in both strength and endurance-trained athletes was not studied. [117]

Following exercise the accompanying decrease in blood pressure may be related to an inhibition in sympathetic activity. Also unknown is whether it is the intensity or the duration of the exercise session that influences BP and autonomic indicators in recovery for 10 recreationally active males. Each subject underwent four exercise sessions of differing durations and intensities, a moderate long session, a moderate short session, a light long session and an intense short session. Individuals with a higher initial BP values showed a more pronounced reduction in BP following exercise, however there was no significant differences in the behavior of the systolic BP with any of the exercise sessions. This confirms that pre-exercise BP measurements are more indicative of post-exercise hypotension than the exercise session. As for the HRV measurements, based on the RMSSD, parasympathetic recovery was slower following intense and moderate exercise compared to light exercise. The lack of difference in the FFT frequency domain measure of the LF/HF ratio following the sessions may be explained by a faster sympathetic withdrawal accompanying the slower parasympathetic recovery. [77]

While those athletes who are highly trained do display a lower resting HR and HRV, research has not established a relationship between these measures and VO_2max [115, 120]. The use of HRV data following maximal exercise is not the best measure of vagal indices with HRR post-exercise being a stronger indicator of parasympathetic return and sympathetic withdrawal [37, 115, 120]. In addition, physiological measures associated with a sedentary population that often displays higher sympathetic activity such as a higher pre-exercise BP as well as higher BMI and sum of skin folds are negatively related to a slower sympathetic withdrawal following exercise [36, 37, 77]. This further explains the cardioprotective effect of training, both endurance and anaerobic, on both the cardiac and ANS [76, 77, 117].

Methodological Considerations

It is difficult to compare HRV analysis from different studies when the methods and/or analysis differ [7]. Protocols involving resting levels utilizing a supine position cannot be compared to the results obtained when subjects are in a seated position as the body posture changes the effects of gravity on the circulatory system [58]. Athletes with different training regiments as well as those with a long history of training can neither be compared to each other nor to sedentary individuals [7]. Recovery from maximal exercise, such as a VO_2max test, cannot be compared to recovery from a submaximal, interval or strength training protocol as the metabaroreflexes have a greater influence on the parasympathetic nervous system following maximal exercise than submaximal exercise [8, 99]. The length of time of the data collection must also be considered, as shorter durations may not be sensitive enough to detect changes in sympathetic activity [7, 9]. For athletes, the data from RMSSD is preferred over spectral analysis as shorter duration can be utilized with the influence of respiratory rate removed [7-9]. The RMSSD is also deemed more reliable than spectral indices in determining sympathovagal balance in highly trained athletes [8]. Increased acetylcholine saturation in these athletes can be reflected in the high frequency spectral analysis making this analysis insensitive to the effects of training [7].

Heart rate variability is often used to study training load. A moderate increase in training might lead to an increase in HRV, however a large increase in training load will cause a decrease in HRV. This may be due to a saturation of acetylcholine (AcH) receptors in the parasympathetic nervous system, resulting in a decrease in HRV with a corresponding decrease in resting HR in a well-trained athlete. Conversely, as competition approaches and taper is utilized, a decrease in HRV may potentially reflect that an athlete is ready to perform and not that they are overtrained for the event. Methods of analysis of HRV, including length of recording and type of analysis (time domain or frequency domain) are an important consideration for determining change. Using both resting HR and the Ln RMSSD to R-R interval ratio, which considers changes in both vagal tone and vagal modulation, can determine if the changes are due to saturation as opposed to overtraining. Because HRV will change from day to day with an athlete who is training, a one time resting HRV measurement cannot be used to determine assess change, be it positive or negative. It has been suggested that averaging the data points of HRV over one training week to give a more meaningful representation of the HRV changes. Morning rested HRV measures taken over one week have been shown to best reflect the status of an athlete's autonomic balance compared to an isolated measure. The use of consistent tracking can best monitor changes in a single athlete more so than comparisons to previous data. [7]

Athletes involved in a long competitive season have to choose between recovery from the most recent competition and rebuilding fitness or maintaining training to capitalize on adaptations. While many factors go into deciding on the training plan, a lack of full recovery in a fatigued athlete can lead to overreaching and potentially to injury. Daily HRV measures were taken for triathletes in a control and an overreaching training program (n= 8 control, n=16 overreaching) and used to determine if daily or weekly monitoring was more effective for investigating potential ANS changes related to overreaching. Subjects underwent the same initial three week training program followed with a one week taper. Then the control group followed the same protocol for another three weeks while the overreaching group underwent a three week overload phase of a 40% increase in training. Both groups ended with another taper week. Recordings of HRV were taken each morning in both the supine and standing position after awakening and perceived fatigue was assessed weekly using a scale from 1-100 (no fatigue to maximum fatigue). In the overreaching group, 15 of 16 displayed a decrease in performance and a high level of perceived fatigue after the overload period while all 15 showed supercompensation with improved performance after the subsequent taper period. The HR and HRV values were taken either in isolation (single day) or as a weekly average. Weekly averages of HRV upon waking indicated a progressive increase in parasympathetic modulation during the overload period, which was strengthened by the lower HR values during exercise and a progressive decrease in resting HR. The isolated daily data collections were less sensitive to these changes. One limitation of this study was the inability to control for additional stressors that may have affected the HRV data collection. [6]

Utilizing the concept of HRV guided endurance training, 40 subjects were recruited for either the experimental group (n=13 completed) or a control group (n=18 completed) of traditional training with no adjustments made based on resting HRV. The HRV guided group recorded four minutes of resting levels each morning in the supine position with a rolling seven day average being used to guide the changes. The SWC of ±0.5 SD from established values for each subject was used to determine if the subject rested instead of performing their prescribed workout. The subjects in the experimental group improved in 3000m running compared to the control group even with performing less moderate and high intensity training sessions. The improvement in maximal running performance was 2.1% in the experimental group and only 1.2% in the control group, which was not statistically significant however it does have some practical significance in terms of performance. One of the subjects in the experimental group failed to improve and consistently presented with RMSSD values below the SWC due to work stress. This was a challenge to the HRV-based training program that did not have any provisions for monitoring non-training stresses. With this protocol improvements in training can be based on individual variations, such as those based on age and gender, which may prove more successful over traditional training plans. It was noted that the SWC might need to be updated as training adaptations to the ANS and cardiovascular system occur. A potential limitation of the study was that the at home HRV measurement tool may not have been as standardized as those performed in a laboratory setting. [69]

One of the concerns with daily HRV monitoring of elite athletes is the saturation phenomenon and its effect on the LnRMSSD to RR interval relationship. In those who have a resting HR lower than 50 beats per minute HRV interpretation can be misleading leading to misinterpretation of overreaching if the associated vagal saturation response is not considered. Elite rowers (n=3 female, n=1 male) were monitored for seven weeks prior to the 2015 World Rowing Championships. All subjects underwent similar volumes of training. Supine morning HR measurements were taken using the Polar Bluetooth H7 heart rate sensor with data automatically sent to a smartphone via an iPhone application (Igtimi HRV) then uploaded from the smartphone to the researchers for analysis. Individual baseline data was established in the first week of training and change was calculated within-subject as baseline-to-week differences expressed as standardized mean differences or effect sizes that were assessed using a magnitude of change approach. The SWC in LNRMSSD and resting HR was considered 0.5 of the individual baseline coefficient variation and 2% respectively. All rowers displayed a decrease in LNRMSSD to RR ratio at some point during the training, typically between weeks four, five or six yet all rowers were world champions in their respective events. This highlights in association between a decrease in HRV and readiness to perform. The state of functional overreaching contributes to enhanced performance when the training load is reduced. Low LNRMSSD values combined with low resting heart rate can be explained by parasympathetic saturation. Increases in vagal activity are not necessarily indicative of improved performance but of positive adaptation to training. It is also important to consider the type of athlete, their own relationship between LNRMSSD and RR intervals and current training regiment. [65]

Another methodological consideration is the appropriate length of recording. Typically it is recommended to take five minutes of resting HRV in athletes in response to rest and physical stress. Previous research on other populations has determined that ultra-short-term Ln RMSSD measures agree with a five minute recording and was therefore applied to an athletic population.

In the resting, pre-exercise condition, randomly selected 10, 30 and 60 second recordings had no significant difference when compared to the five minute recordings for Ln RMSSD (ICC of near perfect to very large). The post-exercise (Bruce protocol, VO_2max) condition, the comparisons were significantly different, however the effect size was small and the ICC was nearly perfect. It is possible that the shorter time period did not provide an appropriate number of R-R intervals for HRV determination in the post-exercise condition and that the lack of steady state in recovery provided too little variation in the R-R intervals during the 10 and 30 second conditions. The 60 second recording is recommended as an acceptable alternate to a five minute recording in athletes both at rest and in post-exercise recovery. [9]

When a subject is in the supine position, HRV is regulated predominantly by parasympathetic neural influence while the standing position is associated with higher sympathetic neural influence. Elite male (n=7) and female (n=11) sprinters underwent supine and orthostatic (standing) HRV data collection. Collections were taken on the same day during the final week of general preparation for Olympic qualifying. The standing position resulted in higher cardiac autonomic stress than the supine position for both genders for both the time and frequency domain measures. The standing position results in baroreflex adjustments to accommodate a need for increased blood pressure against gravity and reduces the effect of parasympathetic saturation. Because most HRV studies involving positioning are done on endurance athletes, it is difficult to make assumptions about the parasympathetic effects of training when the subject is in the standing position, especially for athletes involved in anaerobic training. Training mode is also related to specific autonomic cardiac adaptations. The increased intensity of the training of elite sprinters induces higher autonomic cardiac perturbations, contrary to the changes undergone in endurance athletes who maintain a greater training volume but typically a lower intensity. In this study the males presented more notable changes in autonomic stress than females, which is consistent with younger females having a higher HRV than males. [58]

A systematic review attempted to summarize the literature for the influence of swimming on HRV and its use in evaluating training. A total of 14 articles that examined swimming variables and utilized time and frequency domain measures were analyzed for the systematic review. Some methodological considerations in comparing these studies included the use of different algorithms for analysis, the use of ambulatory devices for post-exercise recordings as opposed to the traditional ECG, thermoregulatory changes that may occur in an athlete related to water submersion and choice of swimwear during activity and for data collection. Studies that involve trained and untrained subjects or subjects that may be involved in a variety of training, for example triathletes, make cross-comparison difficult. Additional concerns include training load or time period. The most interesting finding from the studies in the review is that high and stable vagal activity during preparation indicates a readiness to train or appropriate recovery in swimmers. Performance in professional swimmers is correlated with ANS activity with performance having a significantly negatively related to LF and LF/HF ratio and positively related to HF. [74]

A systematic review of normal HRV data was done to provide a potential source of normative data for a healthy population. Considerations were made for length of time of recording, Task Force recommendations for formats [1] and sample size. When compared between studies, time domain measures showed less variation than frequency domain measures with the largest variation in HF power and when log transformed. Females had lower values for time domain measures and males had lower frequency domain measures for LF and HF power but not LF/HF, which was lower in females. The FFT method had lower LF power, higher HF power (log transformed and absolute) and higher LF/HF ratio. Many studies fail to report mean HR and mean RR, which was seen as a fundamental flaw in the reporting of HRV. Underlying factors in HRV analysis that lead to discrepancies include participation in physical activity, paced breathing protocols (especially with physically active individuals), age and gender of the participant, the use of differing frequency bandwidths, poor RR interval editing and a failure to recognize normal or abnormal values in healthy participants.[34]

Measures of HRV have been validated under resting conditions and cannot be directly compared to measures taken during exercise. These measures are based on parasympathetic activity, which is withdrawn during exercise and baroreflex activity, which is altered in the exercise state. At higher exercise intensities, HRV becomes difficult to interpret as the decrease in variability may be limited by the available resolution of the systems used in analysis. The reductions in HF percentage at lower exercise intensities may accurately reflect the withdrawal of parasympathetic activity, however with increasing exercise intensity comes an increased influence in sympathetic activity. This should then be reflected in the LF percentage increasing, yet higher intensity has been associated with a complete removal of LF from the power spectrum, contradicting the findings of pharmacological induced changes in sympathetic activity. It is therefore recommended that further validation of correct methodology for exercise measures should be made. Any direct comparison of resting or pharmacological measures and exercise measures should be avoided. [121]

There are many advantages to using HRV to monitor the ANS status as it is noninvasive, not expensive, time-efficient, and can be applied to a large number of athletes. Ideally HRV data collection for athletes should be taken for five to ten minutes, rested with the athlete in the supine position and time domain indices such as RMSSD should be used for analysis. While research has examined HRV during exercise, its use does not appear to have any practical application and is not as sensitive to fatigue as resting HRV measures. Post-exercise HRV analysis is related to exercise intensity and becomes redundant with exercise HR. A better determinant of recovery and a more relevant monitoring tool appears to be HRR, however more research is needed for confirmation among a wider range of athletes in different sports. Day-to-day variations in training load influence ANS activity with intense exercise decreasing vagal related indices for 24-48 hours while low-intensity exercise increases vagal tone. Therefore HRV monitoring can be used to guide training as long as care is taken to account for training load. This monitoring is straightforward for endurance sports, however monitoring of athletes involved in team sports remains to be evaluated. In the absence of fatigue or overload, decreases in vagal related indices may still occur. This mechanism is likely related to saturation of the acetylcholine receptors, as increased vagal tone gives rise to sustained parasympathetic control of the sinus node thereby decreasing vagal related HRV indices which only the magnitude of the modulation in outflow. Examining the R-R intervals can determine if the changes are truly sympathetic or are related to saturation. With saturation the R-R intervals will increase indicating a lower HR in contrast to increased sympathetic activity, which will be characterized by a higher HR. Daily HRV monitoring can also be beneficial in determining average changes based on training load, however these changes are individualized and comparisons cannot be made between athletes, especially athletes of different sports. When it comes to monitoring athletes, the normal variation, such as day-to-day variability is measured by typical error TE as expressed by a coefficient of variation CV while the changes that have a practical effect are the SWC. Defining the SWC likely depends on the training context, type of adaptations to be monitored and the monitored variable itself. Examining the effects of training over a few points during the training cycle, which represents a bell-shaped curve may result in a wash-out effect of the SWC while frequent monitoring will allow for a better estimate of change over time. The inclusion of home-based monitoring and the ability to data collect multiple times a week upon wakening may be the best option for monitoring the SWC during a training cycle. [8]

The HRV measures are becoming more widely utilized in examining training related autonomic and cardiovascular changes [6-8, 69]. Current research has examined the use of daily HRV recordings to monitor the effects of training on the ANS with weekly training values used to alter training sessions [7, 47, 62]. With the current smartphone technology using the proposed methodology for collecting HRV data in relation to subject positioning, time of collection and duration of the sample, has the potential to make HRV data collection more readily available [8, 58, 67, 74, 121]. Having the ability to establish the SWC for the RMSSD would allow athletes from a variety of sports and training methods to utilize HRV to determine their optimal training [8]. Combining physiological data with subjective data would help identify the affect of non-training stresses on the HRV data [6, 8, 69].

Recovery

In order for training to be effective there needs to be an optimum balance between activity and recovery [38, 41]. Athletes often utilize a variety of modalities such as massage, water immersion, stretching, and active recovery in order to recover between sets of an exercise, between sessions on the same day, or from the stresses of training even though the research has not confirmed that these modalities directly lead to any improvement in performance [41, 122-124]. However even if there is no improvement in performance, it is possible that the athlete would be able to at least maintain their performance with adequate recovery [122]. It is also possible that the recovery modalities will have a cumulative effect if consistently utilized during recovery from training [123].

The effects of active recovery and static stretching were compared to passive recovery on performance of high-intensity intermittent exercise in healthy active but not highly trained students (n=10). For the exercise protocol, subjects performed four bouts of supramaximal exercise at 120% of their VO_2max with a five minute recovery between bouts for the intervention and lactate collection. During the active recovery subjects pedaled at 20% of their VO_2max, during the stretching recovery subjects performed static stretches of 20 to 30 second for the hamstrings, hip extensors, triceps surae, quadriceps and hip flexors and during the passive recovery subjects lay supine without any exercise. The percentage of recovery from the active recovery intervention was higher than with the other two types of recovery ($p<0.05$) with three percent superior work compared to stretching and 4 percent superior work compared to passive recovery. It is important to consider the low intensity of the recovery exercise as well as the short duration. This percentage of gain, while small, does reflect the SWC, which might be critical for the outcome of a competition. [125]

Trained female netball players (n=10) followed intermittent-sprint exercise with active recovery, cold water immersion, or contrast bath, three common recovery strategies employed following team-sport training with little evidence to support their effectiveness. Subjects underwent testing for each intervention plus had a passive recovery session. Each testing session consisted of four repetitions of an intermittent sprint interval exercise circuit designed to mimic game conditions. Performance measures of countermovement vertical jumps and sprints were performed before and after each circuit session to determine decrements in speed and power. A recovery intervention was applied following the first session with the subject returning 24 hours after each intervention to repeat the exercise session. The washout period between modality tests was a minimum of five days. While a large effect size was evident for detriments in vertical jump and sprint time prior to the second exercise session with the cold water and contrast bath therapies respectively, there was no significant difference in the performance variables. However the subjects had less of a decline in the second session compared to the passive and active recovery interventions. Even though the changes were not significant, the subjects did report a significantly lower RPE and a significantly lower amount of muscle soreness following these recovery modalities compared to active recovery, which performed at 40% of their VO_2max for 15 minutes may have been too high for these fit but not elite subjects. As there were individual differences in the results of the recovery modalities, it is possible that each athlete could find an intervention that is suited for their individual needs. [122]

Conflicting results on performance, biochemical and inflammatory markers from hydrotherapy studies lead to further research as to the effects of cold water immersion compared to no intervention for endurance trained cyclists (cold water immersion n=10; control n=11) over a 39-day training block. Both groups followed the same training protocol with the cold water immersion group performing four 15 minute immersion sessions a week while the control group refrained from all hydrotherapy. Neither group was allowed any massage intervention however both groups were allowed to stretch *ad libitum*. Sleep/wake patterns were monitored via activity monitors in conjunction with a journal and the RESTQ-Sport was utilized to monitor stress and recovery. Performance measures were used as objective measures. No physiological variables were examined. Neither group had improvements in their global, stress or recovery based on the RESTQ-Sport scores however the experimental group reported what were deemed possibly harmful effects from the cold water immersion compared to the controls. While both groups were negatively affected in the sleep measures, following the taper the experimental group reported a negative influence in total sleep time and sleep latency categories. Negative influenced of the recovery score was seen in the control group but not in the experimental group. The SWC was not calculated for any of the subjective or performance scores. The performance measures of repeat high-intensity sprints, sprint performance and self-selected workloads the experimental group demonstrated a greater increase in performance when compared to the controls. As this study was intended to mimic a real world training scenario, the subjects were not blinded to their intervention and the subjects were matched for belief in recovery as well as fitness, therefore the placebo effect cannot be ruled out. [123]

The simultaneous influence of different recovery methods on professional young soccer players (n=12) during their preseason was examined to determine the most effective recovery method. Post-recovery anaerobic performance was used as an objective measure and rating of muscle pain was used as a subjective measure. On four occasions throughout the preseason, subjects participated in one of the four recovery interventions, aerobic recovery on land, aerobic recovery in the water, seated rest and electrical stimulation, following the morning session of a twice a day training. On the experimental days the coach standardized the morning and afternoon sessions and the subject utilized polar heart rate monitor tracking to ensure that the training session intensity did not vary. Performance measures of squat jump, countermovement jump, bounce jump, and a 10m sprint were evaluated before the first and second training sessions on the experimental days. Subjective measures included an RPE at the end of morning training and a rating of muscle pain (RMP) from 0 to 10 prior to the second session. Mean recovery approached 100% for all of the interventions with the sprint having the lowest percentage.

Significantly lower RMP values for the leg were found with the aerobic recovery on land and the electrical stimulation but not following the aerobic recovery in the water or the resting recovery. Recovery was also evaluated on an individual level with all players showing full recovery on the squat jump following the aerobic activity in the water and on the countermovement jump for the aerobic activity on land and the electrical stimulation recovery sessions. Neither passive nor active recovery induced any differences in anaerobic performance. The limitations for this study make it difficult to transfer from these elite athletes to athletes in other sports or at other fitness levels. In addition, the one-time use of the recovery modality may not have been enough to elicit change, especially the aerobic water recovery that may have been foreign to some individuals. While monitoring subjective and objective measures of recovery have value for both the athlete and the coach, this study did not provide support for any of the interventions. [124]

The use of recovery modalities is highly common among athletes in an attempt to improve performance even though much of the research does not support performance improvements [41, 125]. Research that does not approach statistical significance could be misleading as to the ability of a modality to ensure that the athlete recovers enough to maintain performance [122]. More appropriate recovery studies are needed to assess the SWC among physiological and psychosocial factors as well as the use of the modalities in conjunction with longer training durations as opposed to single exercise sessions [41, 123-125].

Statistical Considerations

The current health model suggests that meaningful change from the patient perspective reflects a reduction of symptoms or an improvement of function, even if those changes fail to meet the therapeutic threshold for recovery [81, 83]. Changes that are to be examined on an individual basis should therefore be subject to different statistical models than methodologies being used to examine group level changes [81, 126]. Choosing the appropriate methodology for health related outcome studies would need to include a valid interpretation of the change in terms of relevance to the patient [126]. The HRV methodologies refer to the SWC, while healthcare measures the minimal important difference, an anchor based measure and the minimal detectable change [82]. Many current HRV studies are choosing to utilize daily data collections and examining for changes that may be considered to be substantially positive or negative versus those that may be unclear [78].

Traditional analysis in evidence-based practice includes inferences that determine if something is statistically significant based on a *P* value, however this does not always accurately determine the real-world importance of the effect. The use of confidence intervals in inferences can serve to more realistically evaluate whether the change is harmful or beneficial versus a change that may be trivial. The changes can be assigned qualitative terms such as possibly harmful or unclear but likely to be beneficial which would then align with quantitative thresholds of for the standard difference in means (the mean difference divided by the between-subject standard deviation (SD)). This calculation has been used recently to calculate daily changes in HRV for endurance athletes. [6, 70, 71]. Confidence intervals can easily be calculated via spreadsheet with the same assumptions about sampling distribution that are used to derive *P* values. More research is needed to determine the appropriate thresholds of change in HRV, both as athletes in a group as well as individual levels of change, and the qualitative categories that would align with the quantitative changes. [78]

There is a distinct difference in health care models between physiological measures that are clinically significant, showing the presence or absence of a disease, and measures lack clinical significance yet demonstrate meaningful change from the perspective of the patient. Measures that do not come directly from the patient fail to accurately assess the health-related quality of life. An individual may see change that is noteworthy in respect to their recovery or treatment even if it would be seen as a measurement error when compared to group mean changes. Therefore, different statistical approaches are suggested for individual and group analyses. The standard response mean (SRM) utilizes standardized units, is independent of sample size and is based on variability of change. It is calculated as the ratio of the individual change to the standard deviation of that change and does not ignore the variation in the change. In this statistic each individual will have different SRM values depending on their own variability of change. The response statistic (RS) is a variation of the SRM that is a bit more conservative than effect size and takes into account spurious change due to measurement error. It is calculated by dividing the difference between pre-test and post-test change by the standard deviation of change among a group of stable patients. A third statistic, the reliable change index (RCI) takes into account the precision of measure and uses cutoffs based on confidence intervals. It is calculated as a ratio of the pre and post-test change to the standard error of the measurement difference, resulting in a larger denominator and a more conservative measure than the standard error of measurement. A cutoff value for the reliable change index is given as 1.96, however modifications have been suggested including an alternate cutoff points to represent a change that provides a better representation of clinical change. The best statistical approach would be one that defines clinically meaningful change. [81]

Depending on the statistical methodology, a clinically relevant change could be one that focuses on the change within the subject from distinct time points or one that focuses on changes between the group mean and subjects at a single point in time. For those in which therapeutic change may not be dramatic, an instrument that is sensitive to change over time would be more appropriate. Measurement of effect size in clinical assessments does not always provide meaning behind the observable change. Improvements in activities of daily living would have a greater perception of change in patients than changes in strength measures. In some cases the direction of the change, improvement versus decline, may be just as important to the patients as degree of change. While accurate reporting of results will include the effect size, it should be used with caution in studies evaluating clinical change. [126]

Anchor-based statistical measures of receiver-operating characteristic (ROC) curve and mean change approach were compared to distribution-based strategies including RCI and a fixed parameter of 0.5 SD. Each statistical measure was used to evaluate the same data sets from two established indices and two established questionnaires for the minimal detectable change and minimal important difference. For these tools the 0.5 SD measure met the criteria for the minimal important difference of small change and the RCI had the best result for those clinically indices looking for a moderate change. The benefit of the 0.5 SD measure is that it is simple and is independent of sample size and can be effective in calculating the minimal detectable change. However, it is difficult to translate this to data with larger or smaller standard deviations. [82]

The RCI was introduced to ensure that clinically significant results were also representative of a reliable change and has been used effectively with many different variations. In chronic patients, consistently detected reliable change resulted in about 0.5 SD from the previous score regardless of the size of the SD and even without significance; with RCI the cutoff score is 1.96 for 95% confidence. It is possible that subjects will never reach significance in change for either score therefore another recommendation is provide adjustments and fluidity when applying the scores clinically. For example, a cutoff score between 1.96 and 0.84 would indicate that a subject is ready for an adjustment to their plan, although they are not fully recovered and ready for return to play whereas a score of -0.84 would indicate a mild deterioration. In the case of HRV, a mild deterioration may indicate that the subject is not fully recovered from the previous day's training, but would not indicate that they are in danger of OTS. [83]

The RCI is often used in psychotherapy research to predict follow-up scores from a baseline score with a potential adjustment for a practice effect. This methodology allows a clinician to determine if the fluctuations in score represent a meaningful change or normal variability in performance. In the absence of a baseline score for the individual, the use of norms from a similar reference group can be used. Comparing RCI to more complex regression models in neuropsychological testing, the RCI was more accurate with correction for practice effects. While there is no assumption of practice effect in HRV, it is important to consider variations based on training type. [127]

When testing the reliability of a measure it is important not only to determine how well the measurement can track change but also the measure will need to be repeated a reasonable number of times in order to determine how much random error or "noise" is present. As a general rule, the larger the value, the larger the error that will be present. In monitoring a single individual, it is important to determine how much normal variation is to be expected in order to understand the appropriate amount of expected change and what is the appropriate amount of error. This is especially true in monitoring athletes. One area of concern includes the reliability of the equipment to produce similar results under similar conditions. The error from the equipment should be kept to a minimum. Limits of agreement, as expressed by the Bland Altman plot, will give a calculation of the range in which an individual's score would fall 95% of the time. Too many measures outside of the limits of agreement would be indicative of a large amount of error and an inaccuracy of either the measurement or the instrument. Changes in the mean scores can be due to either sampling error or the learning effect. Effective studies should limit the learning effect in order to observe true measures of error. The best measure of precision can be given by defining confidence limits, the likely range of the true value. Values that would fall outside of the confidence limits can then be deemed to be from actual change by the intervention as opposed to normal variations or error. [128]

The 0.5 SD measure is often used to establish the SWC in HRV measures, which consistently detected reliable change in chronic medical conditions [82, 83]. Based on current research in smallest clinical change in other disciplines, the RCI, RS and SRM also have the potential to be appropriate statistical measures for recovery [81, 82]. The classification of clinically significant change does not necessarily reflect statistical significance, rather a movement along a continuum from one category to another, which requires there to be organized and defined scores [83]. Consideration to baseline scores, either of the individual or based on group norms, may be applicable in HRV data, however these norms have not yet been established [127].

Appendix A

INFORMED CONSENT FORM

I. INVESTIGATORS

Principle Investigators: Destany D. Gobin, ATC; Kaori Tamura, PhD, ATC, Portia Resnick, MA, ATC, LMT

II. TITLE

HEART RATE VARIABILITY IN COLLEGIATE DIVISION I ATHLETES

III. INFORMED CONSENT

The purpose of this consent form is to provide you with information about this research to help you decide if you would like to participate in this study. Please take your time to review this consent form. If there are any words or sections in this consent form that you do not understand or want to clarify, please do not hesitate to ask the research staff at any time.

IV. WHY IS THIS STUDY BEING DONE?

This study will try to find out more about Heart Rate Variability for Division I Collegiate athletes. It is important to have athletes from all teams and positions because there have been no studies to find normal ranges for a large, highly trainer population.

V. VOLUNTARY PARTICIPATION

A total of 150 participants will take part in this study. You are being asked to participate because you are between the ages of 18 and 25 years old and are a Division I collegiate athlete. It is important to understand that participation in this study is completely voluntary. You may decide not to participate, or withdraw at any time, and it will not affect you in any way. If you decided to participate in this study, you will be asked to sign this consent form. Upon clearance, you will be scheduled for the data collection session. We are asking 50 of the participants to return for a second data collection session, which will be exactly the same as the first. If you are willing to return for a second session, we will schedule you at the end of your first session.

VI. STUDY PROCEDURES

If you decide to participate in this study, you will be asked to attend 1 data collection session. This data collection session will take place in the Human Performance Laboratory at the University of Hawaiʻi at Mānoa. You will have one ECG recording taken. We will measure your height, blood pressure, body mass and you will be asked to fill out a few forms.

The investigator will clean the electrode placement sites and then electrodes will be applied to designated positions. You will rest supine (on your back) or semi-reclined in a comfortable position for 10 minutes and no data will be collected. Then ECG data will be recorded for 15 minutes. At the same time you will place the finger of one hand over the flash of an iPhone in order to capture the same information using the Camera Heart Rate Variability smartphone application.

Should you have any redness or itching at the site of the electrodes prior to the end of data collection, report your symptoms to the investigator immediately and the electrodes will be removed.

VII. RISKS

There is minimal risk of an allergic reaction to the electrodes. Should any redness, swelling, discomfort or irritation occur while wearing the electrodes the electrodes will be removed immediately by the research team.

You will be asked to remain in on your back or semi-reclined position during 1 data collection for approximately thirty minutes. If you are not comfortable due to the position, you can ask to be re-positioned. A certified athletic trainer is available on site to deal with unexpected medical situations that may arise.

VIII. BENEFITS

You may not receive any direct or immediate benefits. However, your participation will help to further understand Heart Rate Variability and the Autonomic Nervous System in highly trained division I collegiate athletes, establishing a baseline for future studies.

IX. COSTS

All clinic and professional fees testing will be provided at no cost to you. Parking fees will be reimbursed to you if needed

X. COMPENSATION

No compensation will be given for your participation.

XI. CONFIDENTIALITY

All information about you will be held confidential to the extent allowed by state and federal law. Your personal information will not be given to anyone outside of the research team without your written permission. A code will be used as identifier instead of your name for this study. Research records that contain personal information, including code key, will be kept in a secure locked file in the Department of Kinesiology and Rehabilitation Science at the University of Hawaiʻi at Mānoa. These documents will be permanently destroyed no later than 5 years after the completion of the study.

Information gathered in this research study may be published or presented in public forums, however your name and other identifying information will not be disclosed. Agencies with research oversight, such as the University of Hawaiʻi Committee on Human Studies Program, have the right to review research records. You would be asked to sign an authorization form to allow the researcher to release any of your personal information obtained through the research process.

XII. INJURY RELATED TO THE STUDY

Should any injury or medical emergency occur during the data collection, first responder care (first aid and CPR) is available, and appropriate referral will be made. First responder care will be provided for free of charge, however, you will be responsible for the cost associated with referral thereafter. If your insurance will not pay for these costs, they will be your responsibility. The University of Hawaiʻi has no program to pay or compensate you in any way for your injuries.

XIII. QUESTIONS

If you have any questions related to the study participation, please contact **Destany Gobin at 251-454-0968 or destany@hawaii.edu**. If you have questions or concerns about your rights as a research participant, please contact the Human Studies Program at (808) 956-5007.

XIV. STATEMENT OF CONSENT

I have read the above information, or it has been read to me. I have had the opportunity to discuss this research study with research staff, and I have had my questions answered by them in a language I understand. I take part in this study of my own free will, and I understand that I may withdraw from participation at any time and this will not affect me in any way. My consent to participate in this study does not take away any of my legal rights in the event of negligence or carelessness of anyone working on this project. A copy of this consent form has been given to me.

XV. SIGNATORIES

I agree to take part in this study.

____
Print Name

____
Signature **Date**

____
Researcher Name (print)

____
Researcher Signature **Date**

Appendix B

INFORMED CONSENT FORM HRV APP ONLY PORTION

I. INVESTIGATORS

Principle Investigators: Yukiya Oba, PhD, ATC, CSCS, Portia Resnick, MA, ATC, LMT, Nicole Kandra, ATC

II. TITLE

Daily HRV and Training Load Monitoring in NCAA Division I Collegiate Athletes

III. INFORMED CONSENT

The purpose of this consent form is to provide you with information about this research to help you decide if you would like to participate in this study. Please take your time to review this consent form. If there are any words or sections in this consent form that you do not understand or want to clarify, please do not hesitate to ask the research staff at any time.

IV. WHY IS THIS STUDY BEING DONE?

This study is being done to track the daily changes in heart rate variability (HRV) and training load in NCAA Division I athletes. The information will be used to develop a formula to monitor daily training and recovery.

V. VOLUNTARY PARTICIPATION

A total of 20 participants will take part in this study. You are being asked to participate because you are between the ages of 18 and 25 years old a Division I athlete. It is important to understand that participation in this study is completely voluntary. You may decide not to participate, or withdraw at any time, and it will not affect you in any way. If you decided to participate in this study, you will be asked to sign this consent form. Upon clearance, you will be given further instructions.

VI. STUDY PROCEDURES

If you decide to participate in this study, you will be asked to use a smartphone application every morning before practice to measure heart rate variability, a tool used to monitor your recovery. You will also be asked to record the duration and type of each practice, along with your rate of perceived exertion and send this information to the researcher after practice each day.

VII. RISKS

The procedures involved in this study no immediate or long-term risks.

VIII. BENEFITS

You may not receive any direct or immediate benefits. However, you may learn more information about your training and recovery from the daily data collection.

IX. COSTS

The Camera HRV iPhone application will be provided at no cost to you. Any incurred data rates are your responsibility.

X. COMPENSATION

No compensation will be given for your participation.

XI. CONFIDENTIALITY

All information about you will be held confidential to the extent allowed by state and federal law. Your personal information will not be given to anyone outside of the research team without your written permission. A code will be used as identifier instead of your name for this study. Research records that contain personal information, including code key, will be kept in a secure locked file in the Department of Kinesiology and Rehabilitation Science at the University of Hawaiʻi at Mānoa. These documents will be permanently destroyed no later than 5 years after the completion of the study.

Information gathered in this research study may be published or presented in public forums, however your name and other identifying information will not be disclosed. Agencies with research oversight, such as the University of Hawaiʻi Committee on Human Studies Program, have the right to review research records. You would be asked to sign an authorization form to allow the researcher to release any of your personal information obtained through the research process.

XII. INJURY RELATED TO THE STUDY

Should any injury or medical emergency occur during the data collection, if your insurance will not pay for these costs will be your responsibility. The University of Hawai‘i has no program to pay or compensate you in any way for your injuries.

XIII. QUESTIONS

If you have any questions related to the study participation, please contact **Portia Resnick at (908) 812-9320 or portia@hawaii.edu**. If you have questions or concerns about your rights as a research participant, please contact the Human Studies Program at (808) 956-5007.

XIV. STATEMENT OF CONSENT

I have read the above information, or it has been read to me. I have had the opportunity to discuss this research study with research staff, and I have had my questions answered by them in a language I understand. I take part in this study of my own free will, and I understand that I may withdraw from participation at any time and this will not affect me in any way. My consent to participate in this study does not take away any of my legal rights in the event of negligence or carelessness of anyone working on this project. A copy of this consent form has been given to me.

XV. SIGNATORIES

I agree to take part in this study.

____

Print Name

____

Signature **Date**

____

Researcher Name (print)

____

Researcher Signature **Date**

Appendix C

Health History Questionnaire

1. Are you or is there a possibility that you may be pregnant?
____

2. Do you have any known tape allergies?
____

If you answered "YES" to any or the above question, you will not be allowed to continue this study

3. Do you have any known cardiac (heart) conditions?
____

4. If you answered yes to #4, please explain.
____

5. Are you currently injured?
____

6. If you answered yes to #5, please explain.
____

7. Do you have diabetes?
____

8. Do you have any neurological disorders?
____

9. If you answered yes to #8, please explain. ____

10. Do/did you have practice before or after data collection? If so, when? ____________________

11. Do you have a game before or after data collection? _____________________________________

12. Do you have an off day from normal physical activity? __________________________________

13. Do you have any academic pressure within a 1-3 days or within 4-7 days? ________________
____

14. Are you in pre-season, post-season, or in season? _______________________________________

Appendix D

R E S T Q – 76 Sport

Single Code: ______________________________ Group Code: _________________________________

Name (Last): _________________________________ (First): ____________________________________

Date: _______________ Time: ______________ Age: _______________ Gender: ________________

Sport/Event(s): ____

This questionnaire consists of a series of statements. These statements possibly describe your mental, emotional, or physical well-being or your activity during the past few days and nights.

Please select the answer that most accurately reflects your thoughts and activities. Indicate how often each statement was right in your case in the past days.

The statement related to performance should refer to performance during competition as well as during practice.

For each statement there are seven possible answers.

Please make your selection by marking the number corresponding to the appropriate answer.

Example:

In the past (3) days/nights

... I read a newspaper

0	1	2	3	4	5	6
never	seldom	sometimes	often	more often	very often	always

In this example, the number 5 is marked. This means that you read a newspaper very often in the past three days.

Please do not leave any statements blank.

If you are unsure which answer to choose, select the one that most closely applies to you.

Please turn the page and respond to the statements in order without interruption.

In the past (3) days/nights

1) *...I watched TV*

0	1	2	3	4	5	6
never	seldom	sometimes	often	more often	very often	always

2) *...I did not get enough sleep*

0	1	2	3	4	5	6
never	seldom	sometimes	often	more often	very often	always

3) *...I finished important tasks*

0	1	2	3	4	5	6
never	seldom	sometimes	often	more often	very often	always

4) *...I was unable to concentrate well*

0	1	2	3	4	5	6
never	seldom	sometimes	often	more often	very often	always

5) *...everything bothered me*

0	1	2	3	4	5	6
never	seldom	sometimes	often	more often	very often	always

6) *...I laughed*

0	1	2	3	4	5	6
never	seldom	sometimes	often	more often	very often	always

7) *...I felt physically bad*

0	1	2	3	4	5	6
never	seldom	sometimes	often	more often	very often	always

8) *...I was in a bad mood*

0	1	2	3	4	5	6
never	seldom	sometimes	often	more often	very often	always

9) *...I felt physically relaxed*

0	1	2	3	4	5	6
never	seldom	sometimes	often	more often	very often	always

10) *...I was in good spirits*

0	1	2	3	4	5	6
never	seldom	sometimes	often	more often	very often	always

11) *...I had difficulties in concentrating*

0	1	2	3	4	5	6
never	seldom	sometimes	often	more often	very often	always

12) ...I worried about unresolved problems

0	1	2	3	4	5	6
never	seldom	sometimes	often	more often	very often	always

13) ...I felt at ease

0	1	2	3	4	5	6
never	seldom	sometimes	often	more often	very often	always

14) ...I had a good time with friends

0	1	2	3	4	5	6
never	seldom	sometimes	often	more often	very often	always

15) ...I had a headache

0	1	2	3	4	5	6
never	seldom	sometimes	often	more often	very often	always

16) ...I was tired from work

0	1	2	3	4	5	6
never	seldom	sometimes	often	more often	very often	always

17) ...I was successful at what I did

0	1	2	3	4	5	6
never	seldom	sometimes	often	more often	very often	always

18) ...I couldn't switch my mind off

0	1	2	3	4	5	6
never	seldom	sometimes	often	more often	very often	always

19) ...I fell asleep satisfied and relaxed

0	1	2	3	4	5	6
never	seldom	sometimes	often	more often	very often	always

20) ...I felt uncomfortable

0	1	2	3	4	5	6
never	seldom	sometimes	often	more often	very often	always

21) ...I was annoyed by others

0	1	2	3	4	5	6
never	seldom	sometimes	often	more often	very often	always

22) ...I felt down

0	1	2	3	4	5	6
never	seldom	sometimes	often	more often	very often	always

23) …I visited some close friends

0	1	2	3	4	5	6
never	seldom	sometimes	often	more often	very often	always

24) …I felt depressed

0	1	2	3	4	5	6
never	seldom	sometimes	often	more often	very often	always

25) …I was dead tired after work

0	1	2	3	4	5	6
never	seldom	sometimes	often	more often	very often	always

26) …other people got on my nerves

0	1	2	3	4	5	6
never	seldom	sometimes	often	more often	very often	always

27) …I had a satisfying sleep

0	1	2	3	4	5	6
never	seldom	sometimes	often	more often	very often	always

28) …I felt anxious or inhibited

0	1	2	3	4	5	6
never	seldom	sometimes	often	more often	very often	always

29) …I felt physically fit

0	1	2	3	4	5	6
never	seldom	sometimes	often	more often	very often	always

30) …I was fed up with everything

0	1	2	3	4	5	6
never	seldom	sometimes	often	more often	very often	always

31) …I was lethargic

0	1	2	3	4	5	6
never	seldom	sometimes	often	more often	very often	always

32) …I felt I had to perform well in front of others

0	1	2	3	4	5	6
never	seldom	sometimes	often	more often	very often	always

33) …I had fun

0	1	2	3	4	5	6
never	seldom	sometimes	often	more often	very often	always

34) ...I was in a good mood

0	1	2	3	4	5	6
never	seldom	sometimes	often	more often	very often	always

35) ...I was overtired

0	1	2	3	4	5	6
never	seldom	sometimes	often	more often	very often	always

36) ...I slept restlessly

0	1	2	3	4	5	6
never	seldom	sometimes	often	more often	very often	always

37) ...I was annoyed

0	1	2	3	4	5	6
never	seldom	sometimes	often	more often	very often	always

38) ...I felt as if I could get everything done

0	1	2	3	4	5	6
never	seldom	sometimes	often	more often	very often	always

39) ...I was upset

0	1	2	3	4	5	6
never	seldom	sometimes	often	more often	very often	always

40) ...I put off making decisions

0	1	2	3	4	5	6
never	seldom	sometimes	often	more often	very often	always

41) ...I made important decisions

0	1	2	3	4	5	6
never	seldom	sometimes	often	more often	very often	always

42) ...I felt physically exhausted

0	1	2	3	4	5	6
never	seldom	sometimes	often	more often	very often	always

43) ...I felt happy

0	1	2	3	4	5	6
never	seldom	sometimes	often	more often	very often	always

44) ...I felt under pressure

0	1	2	3	4	5	6
never	seldom	sometimes	often	more often	very often	always

45) ...everything was too much for me

0	1	2	3	4	5	6
never	seldom	sometimes	often	more often	very often	always

46) ...my sleep was interrupted easily

0	1	2	3	4	5	6
never	seldom	sometimes	often	more often	very often	always

47) ...I felt content

0	1	2	3	4	5	6
never	seldom	sometimes	often	more often	very often	always

48) ...I was angry with someone

0	1	2	3	4	5	6
never	seldom	sometimes	often	more often	very often	always

49) ...I had some good ideas

0	1	2	3	4	5	6
never	seldom	sometimes	often	more often	very often	always

50) ...parts of my body were aching

0	1	2	3	4	5	6
never	seldom	sometimes	often	more often	very often	always

51) ...I could not get rest during the breaks

0	1	2	3	4	5	6
never	seldom	sometimes	often	more often	very often	always

52) ...I was convinced I could achieve my set goals during performance

0	1	2	3	4	5	6
never	seldom	sometimes	often	more often	very often	always

53) ...I recovered well physically

0	1	2	3	4	5	6
never	seldom	sometimes	often	more often	very often	always

54) ...I felt burned out by my sport

0	1	2	3	4	5	6
never	seldom	sometimes	often	more often	very often	always

55) ...I accomplished many worthwhile things in my sport

0	1	2	3	4	5	6
never	seldom	sometimes	often	more often	very often	always

56) …I prepared myself mentally for performance

0	1	2	3	4	5	6
never	seldom	sometimes	often	more often	very often	always

57) …my muscles felt stiff or tense during performance

0	1	2	3	4	5	6
never	seldom	sometimes	often	more often	very often	always

58) …I had the impression there were too few breaks

0	1	2	3	4	5	6
never	seldom	sometimes	often	more often	very often	always

59) *…I was convinced that I could achieve my performance at any time*

0	1	2	3	4	5	6
never	seldom	sometimes	often	more often	very often	always

60) …I dealt very effectively with my teammates' problems

0	1	2	3	4	5	6
never	seldom	sometimes	often	more often	very often	always

61) …I was in a good condition physically

0	1	2	3	4	5	6
never	seldom	sometimes	often	more often	very often	always

62) …I push myself during performance

0	1	2	3	4	5	6
never	seldom	sometimes	often	more often	very often	always

63) …I felt emotionally drained from performance

0	1	2	3	4	5	6
never	seldom	sometimes	often	more often	very often	always

64) …I had muscle pain performance

0	1	2	3	4	5	6
never	seldom	sometimes	often	more often	very often	always

65) …I was convinced that I performed well

0	1	2	3	4	5	6
never	seldom	sometimes	often	more often	very often	always

66) …too much was demanded of me during the breaks

0	1	2	3	4	5	6
never	seldom	sometimes	often	more often	very often	always

67) …I psyched myself up before performance

0	1	2	3	4	5	6
never	seldom	sometimes	often	more often	very often	always

68) …I felt that I wanted to quit my sport

0	1	2	3	4	5	6
never	seldom	sometimes	often	more often	very often	always

69) …I felt very energetic

0	1	2	3	4	5	6
never	seldom	sometimes	often	more often	very often	always

70) …I easily understood how my teammates felt about things

0	1	2	3	4	5	6
never	seldom	sometimes	often	more often	very often	always

71) …I was convinced that I had trained well

0	1	2	3	4	5	6
never	seldom	sometimes	often	more often	very often	always

72) …the brakes were not at the right times

0	1	2	3	4	5	6
never	seldom	sometimes	often	more often	very often	always

73) …I felt vulnerable to injuries

0	1	2	3	4	5	6
never	seldom	sometimes	often	more often	very often	always

74) …I set definite goals for myself during performance

0	1	2	3	4	5	6
never	seldom	sometimes	often	more often	very often	always

75) …my body felt strong

0	1	2	3	4	5	6
never	seldom	sometimes	often	more often	very often	always

76) …I felt frustrated by my sport

0	1	2	3	4	5	6
never	seldom	sometimes	often	more often	very often	always

77) …I dealt with emotional problems in my sport very calmly

0	1	2	3	4	5	6
never	seldom	sometimes	often	more often	very often	always

Thank you very much!

Single Code: ____________ Group Code: ____________

Name (Last): ____________ **(First):** ____________

Age: ________ Gender: ________ Date: ________ Time: ________

Sport/Event(s): ____________

Scoring Key of RESTQ-76 Sport

1 General Stress	2 Emotional Stress	3 Social Stress	4 Conflicts/ Pressure	5 Fatigue	6 Lack of Energy	7 Physical Complaints	8 Success	9 Social Recovery	10 Physical Recovery	11 General Well-Being	12 Sleep Quality
22	5	21	12	2	4	7	3	6	9	10	19
24	8	26	18	16	11	15	17	14	13	34	27
30	28	39	32	25	31	20	41	23	29	43	36*
45	37	48	44	35	40	42	49	33	38	47	46*
Sum	Sum	Sum	Sum	Sum	Sum	Sum	Sum	Sum	Sum	Sum	Sum
Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean

13 Disturbed Breaks	14 Emotional Exhaustion	15 Injury	16 Being in Shape	17 Personal Accomplishment	18 Self-Efficacy	19 Self-Regulation
51	54	50	53	55	52	56
58	63	57	61	60	59	62
66	68	64	69	70	65	67
72	76	73	75	77	71	74
Sum	Sum	Sum	Sum	Sum	Sum	Sum
Mean	Mean	Mean	Mean	Mean	Mean	Mean

*Items 36, 46 have to be inverted for analysis:

(0 = 6) (1 = 5) (2 = 4) (3 = 3) (4 = 2) (5 = 1) (6 = 0).

Appendix E
Training Questionnaire

Subject: ___________________________________

Date: ___________________________________

Sport: ________________________________

Position/event: _________________________

Pre-season In-season Post-season

Number of days per week you practice: _______________

Number of hours per session: ______________

Number of days per week you condition (weight room): ___________

Number of hours per session: _______________

Total number of hours spent training per week: ___________________

Appendix F

Training Log

Subject Number

Date	Practice Type or Game	Length of Time	*RPE

*Rate of perceived exertion (RPE) scale:

#	Level of Exertion
6	No exertion at all
7	
7.5	Extremely light (7.5)
8	
9	Very light
10	
11	Light
12	
13	Somewhat hard
14	
15	Hard (heavy)
16	
17	Very hard
18	
19	Extremely hard
20	Maximal exertion

Notes

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