The use of heart rate variability monitoring for exercise prescription and performance

by

Justin Andrew DeBlauw

B.S., Purdue University, 2012
M.Ed., University of Minnesota, 2013

AN ABSTRACT OF A DISSERTATION

submitted in partial fulfillment of the requirements for the degree

DOCTOR OF PHILOSOPHY

Department of Kinesiology
College of Health and Human Sciences

KANSAS STATE UNIVERSITY
Manhattan, Kansas

2021

Abstract

Background: Results from predetermined exercise programs are typically variable, with high, low, and non-responders being reported. These mixed results are likely due to a lack of individualized exercise prescription. Exercise prescription may be enhanced in real-time through the use of individual monitoring techniques such as autonomic nervous activity via heart rate variability (HRV) or hormone responses. The use of HRV provides insight into how an individual responds to an exercise training load, offering practitioners and coaches valuable information about the individual's adaptations to the overall exercise program. The purpose of this dissertation was to examine the relationship between HRV and other current methods of monitoring individual training responses, the efficacy of HRV to guide high intensity functional training, and whether acute alterations in resting HRV might affect performance.

Methods: This dissertation is composed of three different studies. The first study (N = 8) was a 9-week pilot study examining the relationship between HRV and the testosterone-to-cortisol (T:C) ratio during a high-intensity functional training (HIFT) intervention. Second, we investigated the efficacy of daily HRV to guide the prescription of HIFT during a 9-week intervention with recreationally trained individuals (N = 55). Last, we conducted a quasi-experimental study to evaluate differences in cycling performance between normal and abnormal HRV (N = 25).

Results: During our pilot study we found a negative relationship between HRV and the T:C ratio with large intra-individual variability. Additionally, we showed that HRV had excellent sensitivity (95%), but poor specificity for detecting meaningful changes in the T:C ratio. Secondly, we observed that the use of daily HRV to guide HIFT training resulted in similar cardiovascular, body composition and fitness improvements outcomes with fewer days training at high intensity than predetermined HIFT. Finally, when an individual's daily HRV was outside their normal variation,

decrements in peak power and peak speed were observed during simulated 40-minute cycling time trials.

Conclusion: Our data show that resting HRV may be a clinically utility proxy for indicating hormonal changes during a training intervention. Additionally, we show that HRV is an effective tool for the guidance of HIFT, expanding upon the success of HRV to guide aerobic-based training. Finally, altered daily HRV status may indicate that performance ability is compromised providing support for the notion of decreasing exercise intensity when HRV is outside of normal range. The combined findings from these studies highlight the potential of HRV to enhance exercise prescription through the monitoring of individual training responses by providing practitioners insight into individuals' internal physiological responses to exercise training and implications for performance.

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Acknowledgements

To all of those who fostered my growth over the past four years, thank you. I am forever grateful to family, friends, and mentors who have supported, motivated, and challenged me throughout this process, as this work could not have been completed alone.

Dedication

This dissertation is dedicated to my wife, Amanda DeBlauw, without her encouragement I would never have embarked on this journey. It is because of her support and patience that this has been possible.

Chapter 1 - Introduction

Participation in regular exercise training has numerous beneficial effects on health, physical fitness, and body composition (Hawley et al., 2014; Stone et al., 2007). Exercise training is defined as a subset of physical activity that is planned, structured, and repetitive and has a final or intermediate goal of maintaining or improving physical fitness through physiological training adaptations (e.g., mitochondrial volume, capillary density, and stroke volume) (Caspersen et al., 1985; Hawley et al., 2014). However, individuals following standardized (i.e., predetermined volume and intensity) exercise training programs do not adapt uniformly with a large degree of heterogeneity being observed (Bouchard & Rankinen, 2001). While some individuals display significant improvements in maximal oxygen consumption (VO_2max), resting heart rate (rHR), high-density lipoprotein and systolic blood pressure, others may experience no change or even negative training adaptations (i.e., posttest values below baseline values) (Bouchard & Rankinen, 2001). Standardized exercise training programs do not account for an individual's training age, or the accumulated time and experience from periodic and longitudinal participation in exercise training programs, which can influence the magnitude of realized physiological adaptations (Haff & Triplett, 2015). Additionally, age, sex, baseline fitness, and race have been shown to only account for 11% of the variance following standardized exercise training programs (Bouchard & Rankinen, 2001). Therefore, aggregate mean response reporting does not sufficiently capture the heterogenous individual effects of standardized exercise training programs. With the aim of improving the effectiveness of exercise training programs, specifically in non-responders and negative responders, individualized exercise training programs are necessary (Kiviniemi et al., 2007).

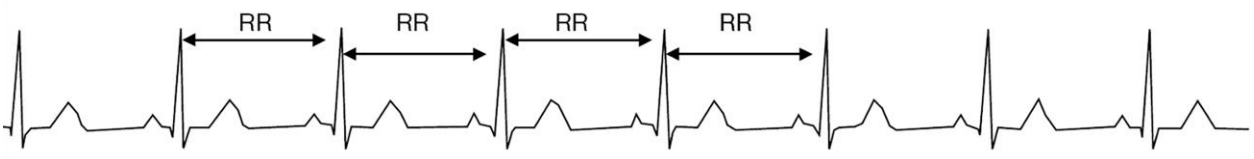
To effectively prescribe individualized exercise training programs, it is essential to determine the optimal training load and recovery time required for positive adaptations. Positive adaptations occur when an individual is exposed to a training stress that is greater than they are accustomed to and disrupts homeostasis followed by a recovery period in which homeostasis can return with a greater fitness level (Campbell et al., 2017). A mismatch between training stress (e.g., insufficient to disrupt homeostasis or too demanding) and recovery can result in undesirable adaptations or fatigue (Campbell et al., 2017). It is therefore essential to employ monitoring strategies to determine whether individuals are adapting to their training program, understand their individual responses to training, assess their fitness and fatigue balance, and reduce the risk of injury and illness (Bourdon et al., 2017).

Exercise scientists are increasing their monitoring efforts to quantify training load, as well as predict and explain the key contributing factors to positive adaptations (Bourdon et al., 2017). In order to optimize training profiles, psychological responses (e.g., mood state), biological markers (e.g. blood lactate), sleep, and nutrition have been monitored in isolation or in combination (Bourdon et al., 2017). Psychological questionnaires such as the Rest Stress Questionnaire for Athletes have been shown to be sensitive to acute (~5–10 days) and chronic (~4-6 weeks) training loads (Foster et al., 1999; Hulin et al., 2016; Saw et al., 2016). Psychological questionnaires are a cost-effective option and can be practically implemented daily with a brief or abbreviated version. However, such questionnaires do not provide insight on an individual's physiological status and run the risk of artificial/fake responses when used as the sole decision-making tool (Bourdon et al., 2017). Additionally, our previous work has shown that a familiarization period is necessary before individual responses to self-report items become accurate (Crawford et al., 2018b).

Heart rate variability (HRV) is a promising inexpensive, time-efficient, and non-invasive method for monitoring adaptations to training via the autonomic nervous system (ANS) (Buchheit, 2014). The ANS consists of the parasympathetic (vagal) and sympathetic branches, which regulate the body's physiologic functions. Sympathetic activity originates from the spinal cord and stimulates all regions of the myocardium. Conversely, the vagus nerve is responsible for parasympathetic control of the heart and innervates the sinoatrial node, atrioventricular node, and atrial myocardium (Aubert et al. 2003). Vagal stimulation decreases heart rate and increases HRV, which refers to the difference in time intervals between the peaks of a QRS complex referred to as the R-R intervals, whereas sympathetic stimulation has the opposite effect (Hainsworth, 1998). Figure 1.1 demonstrates the identification of R-R intervals of successive QRS complexes from an electrocardiogram (Aubert et al., 2003). In summary, it is widely believed that HRV is a valid measurement to assess changes in cardiac autonomic regulation (Billman et al., 2015).

Figure 1.1.

Identification of R-R Intervals from a QRS Complex



HRV has increased in popularity as a tool for planning and adjusting individual training prescription as it is responsive to acute changes in training load (Esco & Flatt, 2014; Pichot et al., 2000, 2002). HRV-guided training prescription is based on the idea that decreases in vagal activity are associated with negative training adaptations, while increases in fitness and performance are related to increases in vagal indices of HRV (Plews et al., 2013). HRV-guided training utilizes

these responses in vagal activity to influence changes in prescribing daily exercise intensity. Our purposed methodology for using smallest worthwhile change (SWC) windows of HRV for the modulation of exercise prescription is displayed in Table 1.1 and further detailed in chapter 3.

Table 1.1.

Proposed Methodology for the Modulation of Exercise Prescription

Within SWC1	Performing training session at prescribed intensity and volume
Between SWC1 and SWC2	Perform training session with a 25% reduction in training volume and intensity
Beyond SWC2	Perform low-intensity, active recovery session (e.g., walking, stretching) for 20-minutes

Note. SWC1- standard deviation*0.5; SWC2- standard deviation*1.0

HRV-guided training has resulted in superior endurance training adaptations in VO_2max, 3000m running performance and maximal running velocity compared to standardized exercise training programs (Kiviniemi et al., 2007; Vesterinen et al., 2016). However, its application to mixed modality training, which more accurately represents current exercise prescription guidelines, as well as its ability to signal a compromised performance, are still inconclusive. The purposes of this dissertation were to determine the relationship between HRV and other current methods of monitoring training load responses (Chapter 2), to determine the efficacy of HRV to guide the prescription of high-intensity functional training (HIFT) (Chapter 3), and to evaluate the impact of acute alternations in HRV on cycling performance (Chapter 4).

Chapter 2 - Evaluating the Clinical Utility of Daily Heart Rate Variability Assessment for Classifying Meaningful Changes in Testosterone-to-Cortisol Ratio: A Preliminary Study

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Summary

The study purpose was to determine the relationship of resting heart rate variability (HRV) and testosterone to cortisol (T:C) ratio, along with the diagnostic ability of HRV to assess changes in T:C ratio during a 9-week high-intensity functional training intervention. Eight recreationally active men (n = 4, age 24.25 ± 1.75 yrs., height 181.25 ± 3.86 cm, weight 79.68 ± 11.66 kg) and women (n = 4, age 26 ± 3.6 yrs., height 164.25 ± 3.3, weight 73.4 ± 8.42) completed daily HRV measurements (HRVdaily) using photoplethysmography via a commercially available smartphone application along with weekly saliva samples. Saliva samples were analyzed for concentrations of testosterone (T) and cortisol (C) via enzyme-linked immunosorbent assays. Upon study completion 72 data points were available, due to participant compliance and inadequate saliva sample, 67 matched pairs of HRV and T:C ratio were analyzed. A statistically significant negative relationship (n = 67, r = -.315, $p < 0.05$) was found between HRVdaily and saliva T:C ratio concentrations within aggregate data. Individual participant relationships showed considerable variability (r = - 0.101 – 0.665, p = 0.103 to 0.829). The model which best explained the data resulted in AIC = 130.247 with factors HRVdaily (β = -0.218, 95%CI = -0.391, -0.044, t = -2.46, $p < 0.05$), Sex (β = 0.450, 95%CI = -0.214, 1.114, t = 1.113, p = 0.242), and Group (β = -0.394, 95%CI = -1.089, 0.302, t = -1.11, p = 0.311). Diagnostically, HRVdaily demonstrates excellent sensitivity (95%), but poor specificity (5%) for detecting meaningful changes in T:C ratio. Assessment of HRVdaily may be a clinically valid proxy measure for monitoring hormonal changes throughout a training intervention.

Introduction

Exercise training represents a significant perturbation to both the human neuroendocrine and autonomic nervous systems (ANS) (Aubert et al., 2003; William & Nicholas, 2005). Well-planned exercise training programs attempt to balance both acute and chronic training loads (TL) in order to maximize physiological adaptation and attenuate the risk of maladaptation (Bourdon et al., 2017; Foster, 1998; Halson, 2014). The imposed stresses from exercise TL can be viewed on a continuum with fatigue anchoring one end and recovery the other (Fry et al., 1991). As such, poor management of TL due to imbalance between training stresses and recovery may increase the risk of injury or lead to a state of non-functional overreaching (Borresen & Lambert, 2008; Mohammadi & Roozdar, 2010). Conversely, effective TL management results in the adaptation of various physiological systems to a higher fitness level (Fry et al., 1991; Hamlin et al., 2019). Practitioners have often faced difficulties in maintaining TL balance as individual responses to acute and chronic exercise are unique. Thus, the ability to monitor TL through objective measures may enhance understanding of individual training responses and reduce the risk of maladaptation (Foster, 1998; Halson, 2014).

Monitoring strategies for quantifying internal TL (i.e., physiological responses to training) include blood lactate concentrations, heart-rate based metrics, and hormonal responses (Borresen & Ian Lambert, 2009; Campbell et al., 2017; Halson, 2014). Exercise-induced hormonal responses are controlled by the hypothalamic-pituitary adrenal axis (HPA), a key regulator of homeostasis, which responds to stress by triggering a series of endocrine changes resulting in the release of testosterone (T) and cortisol (C) (Kim et al., 2018). T is required for protein synthesis and glycogen replenishment, while C inhibits protein synthesis and can lead to immunosuppression (Lee et al., 2017). Thus, the testosterone-to-cortisol ratio (T:C) can be viewed as the balance between anabolic

to catabolic processes (i.e., recovery status/adaptation status) (Schelling et al., 2015; Vervoon et al., 1991) and has been proposed to monitor internal TL, fatigue, training stress, and adaptation (Häkkinen et al., 1987; Mangine et al., 2018). A decrease in the T:C ratio ≥ 30% has been related to incomplete recovery from training (Banfi et al., 1993). The T:C ratio is influenced by training volume (Marx et al., 2001; Schelling et al., 2015) and intensity (Maresh et al., 2006; McGuigan et al., 2004), often decreasing with fatigue (Urhausen et al., 1995). Training programs that have modulated training based on changes in the T:C ratio have shown enhanced performance outcomes in both individual (e.g., sprinting, throwing) and team sports (e.g., soccer) (Handziski et al., 2006; Stone et al., 2007). Thus, the T:C ratio may provide additional insight in both acute & chronic TL-induced stress. Despite its utility, regular assessment of T:C ratio is often infeasible in practical settings as it requires invasive serum or saliva collection and analysis (Twist & Highton, 2013).

A promising non-invasive tool, heart rate variability (HRV), monitors internal TL and adaptation via the ANS and provides valuable insight into fatigue monitoring (Achten & Jeukendrup, 2003; Makivic et al., 2013; Plews et al., 2013). HRV is estimated by measuring the time intervals between successive heartbeats, where an increase or decrease in these intervals reflects cardiac parasympathetic activity (Makivic et al., 2013). Previous studies demonstrate that HRV is sensitive to individual variation in adaptation, fatigue, and overload during exercise training programs (Flatt & Esco, 2015, 2016a; Plews et al., 2013). Current assumptions are that training maladaptation is associated with reductions in cardiac parasympathetic activity and a decrease in HRV (Plews et al., 2013). Conversely, improved fitness is associated with increased cardiac parasympathetic activity and HRV (Plews et al., 2013). Unlike the T:C ratio, HRV appears to provide an easily assessed objective measure for evaluating fatigue when manipulating training prescriptions (Kiviniemi et al., 2007; Plews et al., 2013).

As the ANS and HPA work in tandem to respond to disrupted homeostatic processes, measuring stress responses from exercise training via the highly coordinated and interconnected ANS and HPA pathways (Porges, 1995; Rotenberg & McGrath, 2016). Due to the complex integration of these systems, to date, no single definitive marker can accurately quantify the fitness and fatigue responses to training (Borresen & Ian Lambert, 2009; Bourdon et al., 2017). Currently, the relationship between the ANS and hormonal balance throughout a multimodality exercise program such as high-intensity functional training (HIFT) is not well understood (Feito, Heinrich, et al., 2018). It has yet to be demonstrated if HRV and T:C ratio can identify fatigue in parallel with one another during HIFT. Therefore, the purposes of this study were to determine the relationship between daily resting HRV and pre-exercise T:C ratio and evaluate the clinical utility (i.e., diagnostic validity and reliability) of daily HRV assessment in classifying atypical T:C ratio changes throughout a nine-week HIFT intervention. It was hypothesized that HRV and T:C ratio would have a significant positive relationship and the daily HRV would be a valid surrogate measure for the body's hormonal status.

Methods

Participants

Eight recreationally active men and women ages 18-35 were recruited for participation in the present study. All participants were currently regularly exercising, but not pursuing any specific health or fitness goal (e.g., weight loss or competition preparation) for at least six months prior to study commencement. All participants had previous experience with aerobic (9.1 ± 3.4 years) and resistance training (5.9 ± 3.4 years). All participants were considered a novice in regard to their experience with HIFT. Participant demographic characteristics are presented in Table 2.1. All participants were free of any physical or health limitations that might indicate a

contraindication for vigorous exercise as determined by a medical history questionnaire and physical activity readiness questionnaire (PAR-Q) (Thomas et al., 1992). Additionally, no participants reported taking any medications (e.g. beta blockers) or having any physical conditions that could influence HRV (e.g. atrial fibrillation). This investigation was approved by the University's Institutional Review Board (#9131) and all participants provided written informed consent prior to study commencement. This research was carried out fully in accordance with the ethical standards of the International Journal of Exercise Science (Navalta et al., 2019).

Table 2.1.

Participant Characteristics

	Men (n = 4)	Women (n = 4)
Age	24.3 ±1.75	26.0 ±3.60
Weight (kg)	79.7 ±11.66	73.4 ±8.42
Height (cm)	181.3 ±3.86	164.3 ±3.30
rHR	61.3 ±7.75	68.1 ± 6.30
LnRMSSD	8.7 ±0.63	8.9 ±1.50
T (nmol/L)	1.1 ±0.42	0.5 ±0.23
C (nmol/L)	10.6 ±6.62	9.8 ±7.32
T:C ratio (nmol/L)	0.2 ±0.12	0.1 ±0.08
LnT:C	-2.2 ±0.74	-2.8 ±0.74

Note. rHR– resting heart rate, LnRMSSD- log of root mean squared of standard deviation, LnT:C– log of testosterone to cortisol

Protocol

This study was a secondary analysis of a subset of participants from a larger study (Crawford et al., 2018a). Participants completed baseline demographic information and fitness testing prior to the start of a HIFT intervention. Following 14 days of baseline HRV assessments,

participants were randomized to either a treatment (n = 4) or control (n = 4) condition. Participants began the 60-minute exercise intervention sessions for five consecutive days (Monday-Friday) with two days of recovery (Saturday & Sunday). Two three-week training periods were interspersed between pre, mid and post-performance evaluation weeks, for a total of nine weeks (Crawford et al., 2020). Full description of the study intervention is provided in the Appendix Table A.1. Participants within the control condition completed all training sessions as prescribed. For participants within the treatment condition, training volume and intensity were manipulated based on potential meaningful shifts in resting HRV as previously established (Kiviniemi et al., 2007, 2010; Plews et al., 2013). A participant with HRV falling outside their smallest worthwhile change window 1 (SWC1) reduced their work volume and external load (i.e., absolute weight used) by 25%. A participant HRV falling outside their SWC2 completed an active recovery session (e.g., walking and light stretching) for 20 minutes (Crawford et al., 2020). Participant condition was balanced so that the subsample included two males and two females within each condition. Three training times were offered each day to accommodate participant schedules, and participants were asked to attend the same training time throughout the intervention. Throughout the intervention all participants completed daily resting HRV measurements and provided weekly pre-exercise saliva samples each Friday.

Heart Rate Variability (HRV)

Daily HRV measurements were taken via a commercially available smartphone application for both iOS and Android software HRV4Training (Amsterdam, Netherlands; see http://www.hrv4training.com/). The software utilized photoplethysmography to determine variability in R-R intervals from continuous heart rate data and has been previously validated with electrocardiography (Plews et al., 2017). In order to maintain HRV reliability, participants were

instructed to, upon waking, empty their urinary bladder, and return to a supine position before initiating the reading. Participant were instructed to assess HRV in the supine position for one minute with the index finger covering the smartphone camera and with a respiration rate of 15 breaths per minute (Esco & Flatt, 2014; Plews et al., 2017). The methodology used for signal filtering, processing, interpolation, artifact correction, and R-R peak detection are detailed in the original reference for the applications development (Plews et al., 2017). HRV was collected for two weeks prior to the start of any fitness testing or training protocol in order to establish a baseline. For day-to-day monitoring of individual recovery status (i.e., sympathovagal balance), the root mean squared of successive differences (RMSSD) of R-R intervals was used as it appears to be less influenced by breathing rate and could be assessed validly in only one minute (Esco & Flatt, 2014; Flatt & Esco, 2013, 2016b; Plews et al., 2013; Saboul et al., 2013). Due to the lack of normality, RMSSD was transformed using the natural logarithm (LnRMSSD); it was then multiplied by two so that LnRMSSD (HRVdaily) could be viewed on a scale of approximately six to ten for interpretation purposes and reflect the application's readout (Williams et al., 2017). A meaningful change in LnRMSSD was determined through the use of SWC windows in participants' seven-day rolling average. The SWC was set as ± 0.5 standard deviations from an individual's rolling seven-day LnRMSSD (Kiviniemi et al., 2007, 2010; Plews et al., 2012). Participants continued to measure their HRVdaily for the duration of the study following previously established protocols (Crawford et al., 2020). Participants were asked to complete a total of 75 HRVdaily readings throughout this investigation, the sub-sample averaged a 93.3% adherence to the HRVdaily readings.

Saliva Collection and Analysis

Participants provided saliva samples 15 minutes prior to their training sessions each Friday. Approximately 2 mL of saliva was collected via an oral swab (Salimetrics LLC, State College, PA, USA) and stored in a swab storage tube at -20°C until assay. A total of 70 samples were collected across the eight participants; one sample was lost due to insufficient saliva collection. Participants provided their pre-exercise saliva sample within 5 minutes of starting the standardized 10-minute warm-up. Concentrations of testosterone and cortisol were analyzed via a commercially available, enzyme-linked immunosorbent assay (ELISA) (Salimetrics LLC, State College, PA, USA), following the manufacturer's guidelines. All samples were analyzed in duplicate with an average coefficient of variation (CV) of (4.766%) for testosterone and (5.285%) for cortisol. A 30% or greater decrease in T:C was deemed meaningful and was determined "at risk" (Banfi et al., 1993). T:C values were compared on a week-to-week basis for each participant.

Intervention

The exercise intervention employed within this study followed a popular, community-based HIFT template (Glassman, 2016). All training sessions were conducted as group exercise within the Functional Intensity Training Laboratory (FIT Lab) at Kansas State University. Specific details of the structure and components of each daily training session can be found in the Appendix in Table A.1 Crawford et al., (2018a). All training days included an instructor-led warm-up, a brief movement preparation period, a daily workout, and a cool-down lasting a total of approximately one hour in duration. Thirty training sessions were programmed for participants to complete, with an adherence rate of 80% required for data inclusion. Additionally, participants were asked to not engage in any exercise training outside of the intervention.

Statistical Analysis

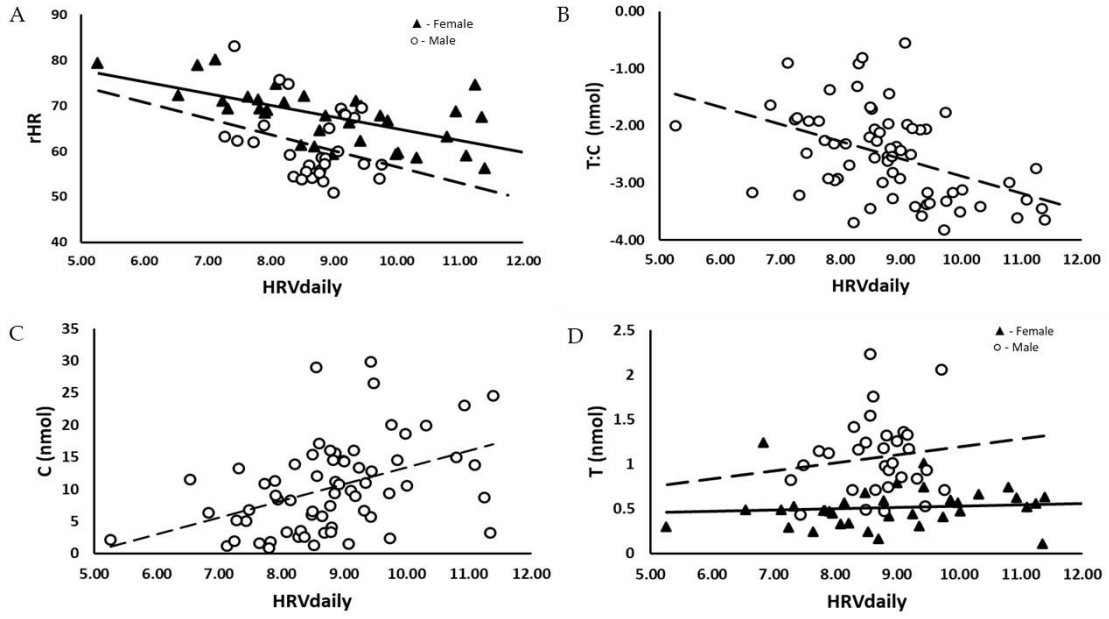
Data were analyzed using the R statistical computing environment and language (v. 4.0; R Core Team, 2019) via the Jamovi graphical user interface (v. 1.6.3; The Jamovi Project, 2020). Data for HRV and T:C ratio were only analyzed if a daily matched pair existed; of the 72 total time points, five were missing a matched pair resulting in an analysis of 67 time points. The HRV and T:C ratio data were checked for normality (Shapiro-Wilk test). The T:C ratio was transformed using the natural log method (lnTC) prior to statistical analysis due to excessive skewness (2.27 ± 0.28) of these data (Crewther et al., 2010). Relationships between HRV and salivary hormone data were assessed using linear mixed-effects models via the GAMLj: General analyses for linear models module (Gallucci, 2019). Potential fixed effects covariates (sex and treatment group) in addition to random effects of time and the individual participant were explored. A model comparison approach was employed using the Akaike Information Criterion (AIC) goodness-of-fit metric to identify an alternative model that best explained the data for each relationship of interest (Judd, 2011). Missing data were treated using pairwise (i.e., available case) analyses and the resulting number of observations for each specific analysis is reported in the results section. An alpha level of 0.05 was used for all statistical inferences. Post hoc assessments were adjusted using the Bonferroni correction. A 2x2 table was constructed to allow the development of estimates for diagnostic validity (e.g., sensitivity and specificity) and reliability (e.g., positive and negative predictive value) of HRVdaily for detecting atypical changes (i.e., >30% T:C ratio concentration) (Portney, 2020). A posthoc power analysis conducted using G*Power 3.1 (Universität Kiel, Germany) determined that with 67 collected samples we achieved 93% statistical power for testing the relationship between resting heart rate and HRV, 80% statistical power for HRV and T:C ratio, and 98% statistical power for HRV, T and C relationships.

Results

A statistically significant negative relationship was observed between HRVdaily and the T:C ratio ($p < 0.05$, $R^2 = -.315$) (Figure 2.1B). The model which best explained the data resulted in an AIC = 130.247 with factors HRVdaily (β = -0.218, 95%CI = -0.391, -0.044, $t = -2.46$, $p < 0.05$), Sex (β = 0.450, 95%CI = -0.214, 1.114, $t = 1.113$, $p = 0.242$), and Group (β = -0.394, 95%CI = -1.089, 0.302, $t = -1.11$, $p = 0.311$) as predictors. A significant main effect for sex (mean difference = -7.18, 95%CI = 2.2, 11.9, $t = 2.88$, $p < 0.05$) was observed in the resting heart rate (rHR) and HRVdaily relationship ($R^2 = .248$, $t = 2.88$, difference = 7.18, $p < 0.05$) (Figure 2.1A). There was no significant relationship found between cortisol and HRVdaily ($R^2 = .249$, $t = -1.76$, difference = -5.29, $p = 0.167$) (Figure 2.1C), and neither sex nor group were significant factors. A significant main effect for sex (mean difference = -6.82, 95%CI = .72, 1.07, $t = -6.82$, $p < 0.05$) was observed for the T and HRVdaily relationship ($R^2 = .42$, $t = -0.56$, $p < 0.05$) (Figure 2.1D).

Figure 2.1.

Regression Plots



A) rHR and HRVdaily, B) T:C and HRVdaily, **C**) C and HRVdaily and **D**) T and HRVdaily

HRVdaily: log of root mean squared of successive differences. All raw data and summary statistics are reported in Table 2.2. Within-participants the HRVdaily and T:C ratio relationships varied from weak to strong (R^2 = - 0.101 to 0.665, p = 0.103 to 0.829).

Table 2.2.

Individual Participant Data

Participant 1 (woman)-control	TP 1	TP 2	TP3	TP 4	TP 5	TP 6	TP 7	TP 8	TP 9
LnRMSSD	6.54	7.95	7.90	-	8.14	8.87	8.21	6.83	7.32
Testosterone (nmol/L)	0.49	0.54	0.47	-	0.57	0.42	0.34	1.24	0.53
Cortisol (nmol/L)	11.59	8.43	9.04	-	8.28	11.20	13.97	6.36	13.24
T:C ratio	0.042	0.064	0.052	-	0.069	0.038	0.024	0.195	0.040
Participant 2 (woman)-control	TP 1	TP 2	TP3	TP 4	TP 5	TP 6	TP 7	TP 8	TP 9
LnRMSSD	5.26	8.52	7.12	7.82	8.78	7.64	8.08	7.24	7.80
Testosterone (nmol/L)	0.30	0.24	0.49	0.48	0.59	0.24	0.33	0.29	0.48
Cortisol (nmol/L)	2.17	1.33	1.21	1.90	7.41	1.61	3.32	1.95	0.88
T:C ratio	0.138	0.180	0.405	0.253	0.080	0.149	0.099	0.149	0.545
Participant 3 (man)-control	TP 1	TP 2	TP3	TP 4	TP 5	TP 6	TP 7	TP 8	TP 9
LnRMSSD	7.48	8.28	9.07	8.30	8.57	8.80	8.49	8.79	8.36
Testosterone (nmol/L)	0.99	0.71	0.85	1.42	1.54	0.98	1.24	0.47	1.16
Cortisol (nmol/L)	6.76	2.62	1.48	3.53	12.07	4.15	6.58	3.32	2.60
T:C ratio	0.146	0.271	0.574	0.402	0.128	0.236	0.188	0.142	0.446
Participant 4 (man)-control	TP 1	TP 2	TP3	TP 4	TP 5	TP 6	TP 7	TP 8	TP 9
LnRMSSD	7.43	9.45	8.86	9.11	9.32	8.14	8.93	9.16	-
Testosterone (nmol/L)	0.43	0.53	0.93	1.36	0.84	-	1.01	1.33	1.09
Cortisol (nmol/L)	5.13	12.81	15.62	9.87	6.66	-	10.76	16.09	4.98
T:C ratio	0.084	0.041	0.060	0.138	0.126	-	0.094	0.083	0.219
Participant 5 (woman)-treatment	TP 1	TP 2	TP3	TP 4	TP 5	TP 6	TP 7	TP 8	TP 9
LnRMSSD	9.74	10.79	11.39	9.98	9.43	10.93	11.09	9.86	10.31
Testosterone (nmol/L)	0.41	0.74	0.63	0.57	1.01	0.62	0.52	0.60	0.66
Cortisol (nmol/L)	2.36	14.96	24.62	18.64	29.82	23.02	13.83	14.55	19.90

T:C ratio	0.174	0.049	0.026	0.031	0.034	0.027	0.038	0.041	0.033
Participant 6 (woman)-treatment	TP 1	TP 2	TP3	TP 4	TP 5	TP 6	TP 7	TP 8	TP 9
LnRMSSD	11.24	8.69	11.35	8.99	9.42	9.24	9.35	10.01	8.48
Testosterone (nmol/L)	0.56	0.16	0.11	0.79	0.74	0.44	0.31	0.47	0.68
Cortisol (nmol/L)	8.70	3.24	3.25	14.48	5.77	13.35	11.01	10.60	6.09
T:C ratio	0.064	0.049	0.034	0.055	0.128	0.033	0.028	0.044	0.112
Participant 7 (man)-treatment	TP 1	TP 2	TP3	TP 4	TP 5	TP 6	TP 7	TP 8	TP 9
LnRMSSD	8.65	9.76	9.48	8.61	9.72	9.18	9.00	8.83	-
Testosterone (nmol/L)	0.71	0.71	0.93	1.76	2.06	1.17	1.26	1.32	0.69
Cortisol (nmol/L)	5.82	20.03	26.47	17.10	9.39	8.97	14.31	14.58	4.70
T:C ratio	0.122	0.035	0.035	0.103	0.219	0.130	0.088	0.091	0.147
Participant 8 (man)-treatment	TP 1	TP 2	TP3	TP 4	TP 5	TP 6	TP 7	TP 8	TP 9
LnRMSSD	7.73	7.28	8.78	8.56	-	7.89	8.85	8.49	-
Testosterone (nmol/L)	1.15	0.82	1.18	2.23	0.85	1.12	0.74	0.49	-
Cortisol (nmol/L)	10.91	5.24	16.12	29.02	15.03	11.28	9.40	15.46	-
T:C ratio	0.105	0.156	0.073	0.077	0.057	0.099	0.079	0.032	-
Mean Data	TP 1	TP 2	TP3	TP 4	TP 5	TP 6	TP 7	TP 8	TP 9
LnRMSSD	8.01	8.84	9.24	8.77	9.05	8.84	9.00	8.65	8.46
Testosterone (nmol/L)	0.63	0.55	0.69	1.23	1.03	0.71	0.72	0.78	0.76
Cortisol (nmol/L)	6.68	8.58	12.2	13.5	11.8	10.5	10.4	10.4	7.48

Table 2.3 presents the diagnostic ability of HRVdaily for assessing unfavorable changes in the T:C ratio concentration. This method of HRVdaily assessment demonstrated strong sensitivity (95%), but poor specificity (5%) for detecting meaningful changes in T:C ratio. Further, HRVdaily showed an excessively high false-positive rate (95%) yet a preferable rate of false negatives (5%). HRVdaily also demonstrated a reasonable degree of negative diagnostic accuracy; successfully classifying 41 out of 58 (71%) “no risk”, less than a 30% change, T:C ratio days.

Table 2.3. Clinical Utility of HRV and T:C Ratio

Clinical Utility of HRV and T:C Ratio

	T:C Ratio (At Risk)	T:C Ratio (No Risk)
HRV (At Risk)	1	2
HRV (No Risk)	17	41
Measures of Validity and Reliability		
Diagnostic Accuracy	74%	
Sensitivity	95%	
Specificity	5%	
False Positive Rate	95%	
False Negative Rate	5%	
Positive Predictive Value	33%	
Negative Predictive Value	71%	

Discussion

This study evaluated the relationship between HRVdaily and pre-exercise T:C ratio as well as the clinical utility of HRVdaily to detect changes in T:C ratio during a 9-week HIFT intervention. Our results do not fully support our primary hypothesis that HRVdaily and T:C ratio will respond in parallel; however, they do reaffirm the relationship between the ANS and HPA axis in response to physiological stress. This was demonstrated by elevated parasympathetic outflow resulting in an increase in LnRMSSD while the stimulated HPA axis increased cortisol secretion. However, the association between the ANS and HPA axis has high individual variability with men displaying a better HRVdaily and T relationship. Further, in support of our secondary hypothesis, we demonstrate for the first time that a commercially available HRV monitoring application could be used as a proxy measure to evaluate clinically meaningful fluctuations in T:C ratio throughout a high-intensity exercise intervention, particularly for men.

We found that the ANS regulated changes in HRVdaily were negatively associated with the T:C ratio throughout 9-weeks of HIFT. Previous work by Huovinen et al. (2009), revealed a significant positive association between change in HRV, using standard deviation of normal to normal, and T:C ratio. The difference in findings may be partly due to the inability of Huovinen et al. (2009), to collect baseline hormone values resulting in the authors being unable to report the relationship on a single day. Despite Houvinen et al. (2009) demonstrating that improvements in HRV over time may occur with a greater T:C ratio, the single-day relationship is still unclear.

Our findings differ from previous research due to increased cortisol levels displayed by our participants. This is due in part to the applied stressor. Huovinen et al.'s participants were primarily under psychological strain, whereas our subjects completed regular bouts of HIFT that placed them under physiological strain (Huovinen et al., 2009). Previously, HIFT has been shown to produce a physiological overload that increases C levels and significantly reduces the T:C ratio (Mangine et al., 2018). The physiological overload is result of the high training volume, short rest intervals and varied exercise selection design of HIFT.

The observed positive relationship between C and HRVdaily also is in contrast to findings of Kuorelahti (2019) who studied junior endurance athletes. The elevated cortisol levels we found may in part be due to the lack of HIFT experience within our participants. In contrast, Poderoso et al. (2019), showed decreasing cortisol levels in experienced HIFT participants over a six-month period. Additionally, hormone samples were collected within 15-minutes prior to the start of training therefore it could be speculated that the increase in cortisol may have been due to anticipatory response to enable an improved performance (Passelergue et al., 1995; van Paridon et al., 2017).

Finally, our observed difference in HRV association may be the result of the specific training modality. Kliszczewicz et al. (2016) demonstrated that despite an acute HRV depression following a bout of HIFT, resting HRV values were not altered. It is possible that the ANS stress from HIFT is not sufficient to cause long term disruptions in HRV. Our results demonstrate that during 9-weeks of HIFT the activity of the ANS and HPA-axis were not matched across all individuals. The previously demonstrated positive relationship between HRV and T:C ratio may not hold true across all exercise training programs (Kuorelahti, 2019).

We initially hypothesized there would be a significant relationship between HRV and T:C ratio. If true, this relationship would allow for daily measurement of HRV to serve as a non-invasive proxy for hormonal changes throughout an exercise intervention. As with all diagnostic assessments, we hoped HRVdaily would demonstrate a high degree of both sensitivity (i.e., an ability to rule-out meaningful change in T:C ratio) and specificity (i.e., an ability to rule-in meaningful change in T:C ratio). However, as is common with clinical tests, we were confronted with limitations of HRVdaily for monitoring fluctuations in T:C ratio. In particular, we found a lack of specificity (i.e., 5%) in HRVdaily accurately identifying negative changes in T:C ratio. That is, using resting HRV status missed 95% of the actual "at risk" T:C ratios. However, HRVdaily did demonstrate a high degree (i.e., 95%) of diagnostic sensitivity. Meaning, that if an individual's resting HRV status indicated "no risk" there was a high likelihood that same person's T:C ratio also indicated "no risk." We argue that this finding highlights partial efficacy of HRVdaily to be utilized when a practitioner desires to monitor the hormonal status of his or her athletes in response to a training intervention.

While a test that can both identify "at risk" and "no risk" would be preferred, tests that are good at one or the other still have clinical utility. For example, using HRVdaily, a person can

reasonably infer that when the application indicates they are not at risk they are, in fact, not at risk for maladaptation on that particular day. However, if HRVdaily indicates they are at risk, the person might want to employ a secondary assessment that is more specific to help confirm a meaningful change in T:C ratio. For the recreational athlete, the use of HRVdaily might be able to serve as the sole monitoring strategy of recovery status. As these individuals are typically not concerned with optimal performance and/or adaptation, the consequences of missing a potential training day due to a false-positive "at risk" classification are almost non-existent. Conversely, in high performance environments, a false-positive "at risk" HRVdaily classification would result in an athlete missing a training day and potentially produce suboptimal performance and/or adaptation.

The present study is not without limitations. Throughout the investigation, we asked participants to not engage in any additional exercise outside of the intervention and we were not able to prevent or record additional activities (e.g. supplemental exercise) that could have influenced measured variables (i.e., HRV and T:C ratio). Additionally, sleep quality and duration were not recorded, and participant nutrition was neither controlled nor standardized, all of which could affect T:C ratio and HRV responses. Furthermore, there is the potential that the use of an orthostatic assessment of HRV could have altered our findings as the positive relationship reported by Huovinen et al. (2009) was present during the standing portion of an orthostatic test. Strengths of this investigation included a high (≥80%) adherence rate to training and HRVdaily recordings. Additionally, no participants reported injuries.

Future investigations should attempt to quantify individual and weekly training in order to account for HPA-axis and ANS changes influenced by exercise intensity and volume. Individual T:C ratio should be recorded daily in order to determine if fluctuations in the ANS and HPA-axis

are better related opposed to the summative response to a week of training. As our participants were novices with HIFT, future examinations should determine if these findings are consistent with more experienced participants. As more experienced individuals are typically the ones looking for advanced monitoring strategies to optimize training responses, future results may provide more practical application to this group.

The present study demonstrates an association between the ANS and the HPA axis during 9-weeks of HIFT. Additionally, we demonstrated that HRVdaily is sensitive enough to accurately classify 95% of positive T:C ratios. While these findings indicate HRVdaily may be a useful tool for recreational athletes to monitor recovery status, in more high-performance settings, a more specific secondary test may be needed to ensure valuable training time is not lost due to missing that the athlete was actually “at risk”. These observations further emphasize the potential of HRV for the guidance of training, however, as hormonal responses to training are highly individual the creation of individual ANS and hormonal profiles would increase the accuracy of training stress modulation.

Chapter 3 - High-Intensity Functional Training Guided by Individualized Heart Rate Variability vs. Predetermined Prescription Resulted in Similar Cardiovascular, Body Composition, and Fitness Improvements

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Abstract

Heart rate variability (HRV) may be useful for prescribing high intensity functional training (HIFT) exercise programs. This study aimed to compare effects of HRVguided to predetermined HIFT on cardiovascular function, body composition, and performance. Methods: Recreationally active adults (N = 55) were randomly assigned to predetermined HIFT (n = 29, age = 24.1 ± 4.1 years) or HRVguided HIFT (n = 26, age = 23.7 ± 4.5) groups. Both groups completed 11-weeks of daily HRV recordings, 6-weeks of HIFT (5 d·week-1), and pre- and post-test body composition and fitness assessments. Meaningful changes in resting HRV were used to modulate (i.e., reduce) HRVguided participants' exercise intensity. Linear mixed models were used with Bonferroni post hoc adjustment for analysis. Results: All participants significantly improved resting heart rate, lean mass, fat mass, strength, and work capacity. However, no significant between-groups differences were observed for cardiovascular function, body composition or fitness changes. The HRVguided group spent significantly fewer training days at high intensity (mean difference= -13.56 ± 0.83 days; $p < 0.001$). Conclusion: HRVguided HIFT produced similar improvements in cardiovascular function, body composition, and fitness as predetermined HIFT, despite fewer days at high intensity. HRV shows promise for prescribing individualized exercise intensity during HIFT.

Introduction

Exercise training programs relying on predetermined volume and intensity often result in heterogeneous fitness outcomes across individuals (Bouchard & Rankinen, 2001). To maximize training potential, employing an individualized training program is the most practical applied strategy (Kiviniemi et al., 2010). An important factor in individualizing training and reducing the risk of maladaptation, is the ability to effectively monitor responses to training stressors (Halson, 2014). Training stress is often described as the input variable that is manipulated to elicit a desired physiological response and is categorized as either external (e.g., speed, repetitions) or internal (e.g., heart rate, lactate) load (Bourdon et al., 2017; Impellizzeri et al., 2019).

A promising, non-invasive tool to monitor internal load to optimize training out-comes is heart rate variability (HRV) (Javaloyes et al., 2020; Plews et al., 2013). HRV is assessed by measuring the time intervals between successive heartbeats, wherein an increase or decrease in these intervals reflects changes in cardiac autonomic regulation (Makivic et al., 2013). HRV is a valid tool to assess individual variation in adaptation, fatigue, and overtraining during training programs (Javaloyes et al., 2019; Plews et al., 2013; Vesterinen et al., 2016). Daily HRV measurements are often used to prescribe training in endurance activities such as running (Kiviniemi et al., 2007; Vesterinen et al., 2016), cross country skiing (Schmitt et al., 2018), and cycling (Javaloyes et al., 2019, 2020). Training programs utilizing HRVguided individualization improve VO_2peak, peak power in runners (Kiviniemi et al., 2007), and 40-minute time trial performance in cyclists (Javaloyes et al., 2019).

While these findings are promising, their focus on single modality endurance training regimens does not reflect the complexity of high-level sport training or current trends in exercise programs. High-intensity functional training (HIFT), a “Top 10 Fitness Trend” in 2018, is

comprised of functional, multi-joint aerobic and muscle strengthening exercises performed at relative high effort or intensity (Feito et al., 2018). HIFT combines components of aerobic, weightlifting, and body weight exercises into training sessions in constantly variable patterns across multiple time domains, creating a unique stimulus virtually every day (Crawford et al., 2018a). This uniqueness of HIFT creates difficulty when attempting to quantify training loads with external markers (Crawford et al., 2018a, 2018b). However, HIFT is inherently individually modified as the exercises, intensity levels, and/or time domains can be adapted as needed for each individual (Heinrich et al., 2021). Thus, HIFT programs are ideally situated to benefit from implementing HRVguided training prescriptions.

To the best of our knowledge, no study has investigated the efficacy of HIFT exercise programs when guided by daily HRV. The purpose of the current investigation was to determine the effects of HRVguided HIFT training compared to predetermined HIFT training on cardiovascular function, body composition, and performance outcomes within recreationally active participants. We hypothesized that HRVguided HIFT (i.e., prescribing training volume and intensity of HIFT in response to daily HRV status) would result in reduced training volume at high-intensity and improved fitness out-comes compared to predetermined HIFT training.

Methods

Experimental Design

This study was an 11-week, two-site prospective randomized-controlled trial intervention, designed to determine the efficacy of HRV as means to modulate HIFT. Participants were randomly assigned to either an experimental (HRVguided) or control group (predetermined) with groups balanced for sex. Both sites included an experimental and control group. After assignment, both groups completed 14-days of resting HRV measurements which served as baseline values. Following the baseline period, participants continued taking morning HRV readings and began the

exercise intervention which consisted of two three-week training blocks interspersed with pre- and post-intervention testing weeks; a mid-point week was used to recalibrate HRV metrics. Figure 3.1 illustrates the study timeline. During training weeks, participants completed 60-minute HIFT sessions on five consecutive days (Monday-Friday) followed by two days of recovery (Saturday & Sunday). Participants were asked to participate in 30 total training sessions with multiple training times available during the training intervention as to maintain an appropriate participant-to-researcher ratio and accommodate schedules. The HRVguided group had exercise intensity and volume modulated based on their morning HRV values, while the predetermined group completed training as prescribed. Performance measurements were assessed with participants attending two laboratory sessions during testing weeks with 48 hours of rest in-between.

Figure 3.1.

Study Timeline from Baseline to Post-Testing

<table>
<tr><th colspan="7">Study duration 11- weeks</th></tr>
<tr><td>Weeks 1-2</td><td>Random assignment</td><td>Week 3</td><td>Weeks 4-6</td><td>Week 7</td><td>Weeks 8-10</td><td>Week 11</td></tr>
<tr><td rowspan="2">Baseline HRV & Randomization</td><td>HRVguided</td><td rowspan="2">Pre-testing VO_2max, Strength & Body Composition</td><td>HRV modulated training</td><td rowspan="2">Mid-Point Recalibration of HRV SWC windows</td><td>HRV modulated training</td><td rowspan="2">Post-testing VO_2max, Strength & Body Composition</td></tr>
<tr><td>Predetermined</td><td>Predetermined training</td><td>Predetermined training</td></tr>
</table>

Participants

Fifty-five recreationally active men and women ages 18-35 years were recruited for this study. Site 1 included 25 participants, while site 2 included 30 participants. Participant baseline characteristics sorted by group and sex are presented in Table 3.1. All participants were previously exercising regularly, while not pursuing any specific health or fitness related goal (e.g., weight loss or competition preparation) for at least six months at time of enrollment for this study. All participants reported no physical or health limitations for vigorous exercise as determined by a medical health history questionnaire and physical activity readiness questionnaire (Thomas et al., 1992). Additionally, no participants indicated a health condition or medication that would alter cardiac rhythms. Written informed consent was obtained from all participants prior to study commencement. The study was performed in accordance with the Declaration of Helsinki and two University Institutional Review Boards approved all procedures (IRB #9131).

Table 3.1.

*Participant Characteristics Sorted by Group*Sex*

	Age	**Weight (kg)**	**Height (cm)**
Men (HRVguided) (n=12)	25.0± 5.15	83.4± 10.8	181± 8.64
Men (Predetermined) (n=14)	23.3± 2.84	89.8± 15.5	182± 6.31
Female (HRVguided) (n=12)	22.4± 3.40	72.5± 21.9	164± 5.95
Female (Predetermined) (n=17)	24.6± 4.81	71.8± 9.62	165± 4.81

Heart Rate Variability

All participants took daily morning HRV readings throughout the study using a commercially available smartphone application for both iOS and Android (Amsterdam,

Netherlands; see http://www.hrv4training.com/). The HRV4Training software utilizes photoplethysmography to determine the variability in R-R intervals from continuous heart rate data (Plews et al., 2017). To maintain HRV reliability participants were instructed to use the application in the morning upon waking, after excretion from the urinary bladder and resting for five minutes (Vesterinen et al., 2016). To perform readings, participants placed their index finger over the smartphone camera for one-minute while in the supine position (Esco & Flatt, 2014). The HRV4Training application has a built-in methodology for signal filtering, processing, interpolation, artifact correction, and R-R peak detection which can be found in the reference for the application development (Plews et al., 2017). For day-to-day monitoring of individual recovery (i.e., sympathovagal balance) HRV was measured as the root mean squared of successive differences (RMSSD). Due to the lack of normality, the RMSSD was transformed using the natural logarithm (LnRMSSD), which was then multiplied by two so that LnRMSSD (HRVdaily) could be viewed on a scale of approximately one to ten for ease of interpretation and to reflect application display (Williams et al., 2017).

Resting Heart Rate

Participant resting heart rate (rHR) was collected daily simultaneously with morning HRV readings using photoplethysmography via the HRV4Training smartphone application.

Coefficient of Variance of Heart Rate Variability

Participant coefficient of variation in HRV (CV of HRV), the amount of day-to-day variability in HRV scores, was collected simultaneously with morning HRV readings using photoplethysmography via the HRV4Training smartphone application (Altini, 2019).

Body Composition

Body composition was measured for all participants at pre- and post-testing. Participant height was measured to the nearest 0.1 cm with a Charder stadiometer (Model HM 200P; Taichung City, Taiwan) at both sites. Weight was measured was measured to the nearest 0.1 kg via a Tanita scale (Tanita TBF-140, Tokyo, Japan) at site 1 and Tanita TBF310 bioelectrical impedance scale (Arlington Heights, IL) at site 2. Body fat percentage (BF%), fat mass (FM) and lean mass (LM) were measured using a dual energy x-ray (DEXA; Discovery A QDR, Hologic, Inc., Marlborough, MA) at site 1 and a Tanita TBF310 bioelectrical impedance scale at site 2.

Aerobic Capacity

Aerobic capacity was determined as maximal oxygen consumption (i.e., VO_2max) via the Bruce treadmill test protocol (Bruce et al., 1973). Site 1 used a predictive-regression equation based upon time to exhaustion (Foster et al., 1984) to determine aerobic capacity; the standard error of the estimate for males was ± 3.55 mL/kg/min and ± 2.70 ml/kg/min for females. Site 2 completed the Bruce treadmill test protocol, followed by a maximal oxygen consumption validation to ensure there was no further increase in oxygen consumption with increasing workload (Poole et al., 2008). Indirect calorimetry was assessed through breath-by-breath data recording, measurements were analyzed in 15-second intervals (ParvoMedics TrueOne 2400 Metabolic, Salt Lake City, Utah, USA). The gas calibration and metabolic cart flow were calibrated before each testing session using a 3-L syringe and following manufacturer instructions. Heart rate was recorded continuously using a Polar H7 chest strap heart rate monitor (Polar Electro OY, Kempele, Finland).

Physical Work Capacity

Physical work capacity was measured through a 10-minute workout in which participants completed as many rounds as possible of the following: 12 goblet squats (20 kg kettlebell for men, 12 kg kettlebell for women), 12 burpees, and 24 calories on a rowing ergometer (Model D, PM5 Monitor, Concept 2 Inc., Morrisville, VM, USA).

Muscular Strength

Maximal strength was determined by the one-repetition maximum (1RM) protocol for the barbell back squat, barbell overhead (OH) press and barbell deadlift in kilograms (Butcher et al., 2015) and in accordance with previous research methodology (Crawford et al., 2018a). Individual sum totals for 1RM for back squat, OH press and deadlift were designated as each participant's CrossFit Total (CFT) (Rippetoe, 2006). Each lift was supervised and verified by certified exercise professionals who were also research assistants and participant rest times were controlled with a minimum of three minutes and a maximum of five minutes between maximal attempts (Schoenfeld et al., 2016).

High-Intensity Exercise Training Program

The high-intensity exercise program employed in this study was HIFT, utilizing a popular, community based HIFT template (Glassman, 2016). All training sessions were performed indoors as group exercise and supervised by a research assistant holding a CrossFit® Level 1 certificate. Training sessions for site 1 were held at a community HIFT facility while sessions for site 2 were held within the Functional Intensity Training Lab (FIT Lab) at Kansas State University. The training protocol for this program has been previously described by Crawford et al. (2018a) and specific details of the structure and components for each daily training session can be found in Table A1 within that reference. All training sessions lasted approximately 1-hour in duration and

consisted of an instructor-led warm-up, movement preparation period, daily workout, and cool-down. A total of 30 training sessions were programmed, and an adherence rate of 80% was required for participant inclusion in data analysis. Participants remained in free-living conditions and were asked to not engage in any additional exercise training outside of the study.

Modulation for High-Intensity Exercise Training Program

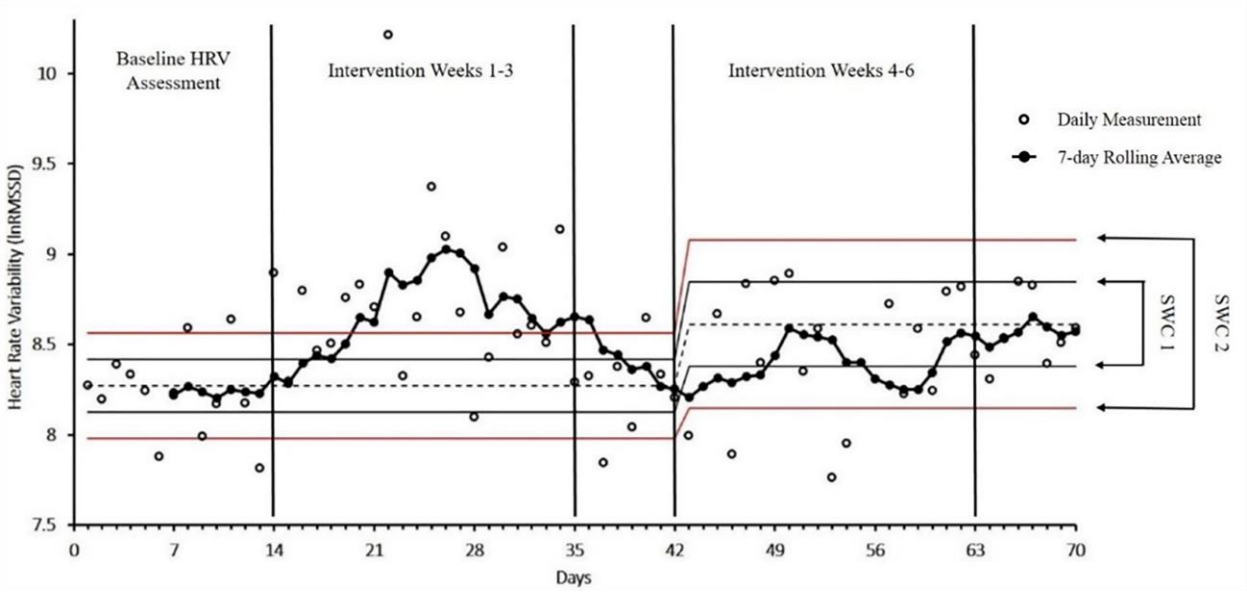
A 14-day baseline period was used to establish individual baseline HRV values. Individual seven-day rolling averages (Ln rMMSD7day) were calculated to determine and track shifts in resting HRV in response to the training. The Ln rMMSD7day was used as it has been demonstrated to be superior in predicting training stress rather than single-day HRV values (Plews et al., 2013). Smallest worthwhile change (SWC) windows were set to monitor meaningful changes from baseline HRV. Previous investigations have established the SWC in resting HRV as ±0.5 standard deviation from an individual's mean Ln rMSSD (Kiviniemi et al., 2007, 2010; Plews et al., 2012; Plews et al., 2013; Vesterinen et al., 2016). For this study, two SWC changes windows were calculated as to ±0.5 standard deviation (SWC1) and ±1 standard deviation (SWC2) from the individual's mean Ln rMMSD in order to modulate training stress during the exercise intervention.

Each HRVguided participant was prescribed reduced training volume and intensity when their rolling seven-day average of HRVdaily (HRV7day as indexed by Ln rMMSD7day) differed meaningfully from baseline values such that it fell within a SWC window (Crawford et al., 2020). When a participant's Ln rMMSD7day was below or above the SWC1 no training modifications were prescribed. If participant's Ln rMMSD7day fell between SWC1 and SWC2, their scheduled workout was reduced 25% in volume (i.e., repetitions) and external load (i.e., absolute weight). If the participant's Ln rMMSD7day exceeded the SWC2, they completed a low-intensity (i.e., >50% HRR) active recovery session (e.g., walking and light stretching activities) for a fixed duration of

20-minutes. A visual representation of HRV monitoring throughout the study is presented in Figure 3.2. The HRV values obtained during the baseline period were used for the first block of training. After the pre-intervention testing and three weeks of training (15 training sessions) HRV means and both SWC monitoring windows were recalculated for the second training period, as previous findings have demonstrated how changes in fitness may alter resting HRV (Boutcher et al., 2013; Buchheit et al., 2010; Hynynen et al., 2010) and the dose of completing 15 HIFT sessions should be sufficient to elicit fitness improvements (Crawford et al., 2018b; Drake et al., 2017; Heinrich et al., 2015). The Predetermined group completed all training sessions without intensity modulation.

Figure 3.2.

Representation of the Longitudinal Monitoring of Heart Rate Variability throughout Study Protocol



Statistical Analyses

Data were analyzed using the R statistical computing environment and language (R Core Team, 2020) via the Jamovi graphical user interface (The Jamovi Project, 2020). Descriptive statistics were calculated, and all dependent variable data were checked for normality prior to inference testing. Relationships between fixed effects (i.e., group and timepoint) and outcome metrics (i.e., cardiovascular, body composition, and performance) data were assessed using linear mixed-effects models via the GAMLj: General analysis for linear models module (Gallucci, 2019). Individual participants were input as random factors within the models and lean body mass was used as a covariate due to significant correlations identified with outcomes metrics. An alpha level of 0.05 was used for all statistical inferences. Post hoc assessments were adjusted using the Bonferroni correction. Effect sizes (ES) were calculated for within and between group changes. ES were classified as 0.2 "small," 0.5 as "medium," and 0.8+ as "large" (Cohen, 1988).

Results

Baseline and post-test values for each training group are shown in Table 3.2. The HRVguided training resulted in similar changes in cardiovascular function, body composition, and performance as the predetermined training (Table 3.2 & Figure 3.3). The greatest percent changes were for predetermined BF% (15.7% decrease) and FM (15.1% decrease), and HRVguided squat (14.2% increase) and deadlift (12.6% increase). The HRVguided group completed significantly fewer days at high intensity than the predetermined group, as shown in Table 3. Participants displayed a high training and dailyHRV monitoring adherence (Table 3.3).

Table 3.2.

Within and Between Group Comparison of Pre- and Post-Test Changes in Key Outcomes

	HRVguided				**Predetermined**				**Between group**
	Pre	Post	% change	ES	Pre	Post	% change	ES	ES
Cardiovascular function									
Resting heart rate (bpm)	73.6± 9.8	69.3± 9.0	-5.8	0.46	74.6± 14.6	72.7± 11.4	-2.6	0.15	0.33
Heart rate variability	8.4± 1.1	8.6± 1.1	2.4	0.14	8.7± 1.2	8.7± 1.2	0	0.01	0.09
CV of HRV	10.1± 3.9	9.0± 3.8	-10.9	0.28	8.7± 3.3	9.5± 3.1	9.2	-0.24	0.14
Body composition									
Body fat %	31.8± 11.1	29.2± 9.7	-8.2	0.63*	31.8± 8.3	26.8± 8.1	-15.7	0.61*	0.27
Lean mass (kg)	54.5± 13.5	54.8± 13.3	0.6	0.02	52.6± 11.2	54.0± 11.5	2.7	-0.12	0.06
Fat mass (kg)	23.9± 8.8	23.5± 8.7	-1.7	0.05	23.9± 8.8	20.3± 8.5	-15.1	0.42	0.37
Fitness outcomes									
VO2max (ml*kg*min)	42.1± 6.8	43.0± 7.5	2.1	0.13	44.4± 6.4	44.2± 8.0	-0.5	0.03	0.15
Work capacity	131± 36.5	147± 35.1	12.2	0.45	127± 24.9	145± 26.3	14.2	-0.70*	0.06
Squat (kg)	90.2± 44.5	103± 45.0	14.2	0.29	87.6± 33.2	99.1± 31.5	13.1	-0.36	0.10
Press (kg)	41.6± 18.9	45.3± 21.4	8.9	0.18	41.5± 16.2	45.5± 16.4	9.6	-0.25	0.01
Deadlift (kg)	103± 46.1	116± 47.2	12.6	0.27	107± 34.8	121± 47.2	13.2	-0.34	0.11
CrossFit total (kg)	232± 109.0	259± 108.0	11.6	0.25	237± 82.2	266± 85.2	12.2	-0.35	0.07

Note. Values are presented as means ± SD. *moderate effect size. VO2max, maximal oxygen consumptions; ES, effect size

Table 3.3.

Study Intervention Metrics by Group

	HRVguided		Predetermined		Between group
	Mean	95% CI	Mean	95% CI	ES
Days at high intensity	12.9± 5.6	11.7; 14.1	26.5± 2.6	25.4; 14.1	3.12**
Training adherence	86.8± 9.5	84.3; 89.0	89.8± 7.6	87.5; 92.0	0.35
HRV compliance	95.1± 4.8	93.8; 96.7	94.6± 5.9	92.9; 95.6	0.09

Note. Values are presented as means ± SD. **large effect size. CI, confidence interval; ES, effect size

Effects on Cardiovascular Function

A significant main effect was found for time were observed for HR (F = 4.89; mean difference = -3.25 ± 1.47 bpm; 95% CI = -6.14, -0.37; p = 0.035) with a reduction in resting HR being observed across both conditions from pre to post test. No other main effects on cardiovascular function were observed.

Effects on Body Composition

Significant main effects for time were observed for LM (F = 16.43; mean difference = 1.19 ± 0.29 kg; 95% CI = 0.61, 1.77; p < 0.001) and FM (F = 4.39; mean difference = -0.62 ± 0.3 kg; 95% CI = -1.12, -0.36; p = 0.045) with all individuals improving LM and FM at post-test. No other main effects on body composition were observed.

Effects on Performance Outcomes

Significant main effects for time were observed for work capacity (F = 14.92; mean difference = 16.87 ± 4.37; 95% CI = 8.31, 25.44; p < 0.001), squat (F = 29.16; mean difference= 7.98 ± 1.48 kg; 95% CI = -5.08, 10.87; p < 0.001), OH Press (F = 10.52; mean difference = 2.62 ± 0.81 kg; 95% CI =1.04, 4.20, p < 0.003), deadlift (F = 22.09; mean difference = 10.37 ± 2.21 kg;

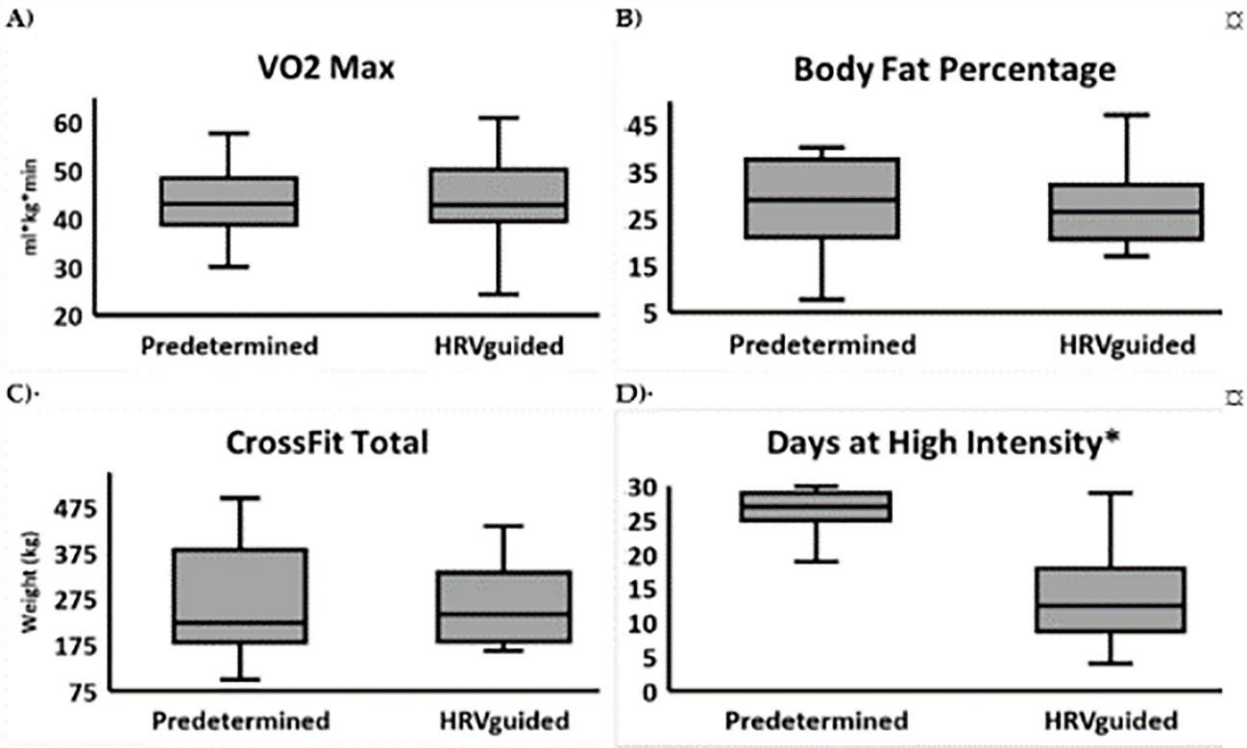
95% CI = 6.05, 14.70; p < 0.001), and CFT (F = 20.68; mean difference = 21.79 ± 4.18 kg; 95% CI = 13.61, 29.88; p < 0.001) where both groups improved at post-test. No other main effects on performance outcomes were observed.

Effects on Intervention Metrics

A significant main effect for group was observed for DHI (F= 270.46; mean difference = -13.56± 0.83 days; 95% CI= -15.20, -11.99; p < 0.001) with the HRVguided group training fewer DHI. Training adherence to the 30 prescribed training sessions for the Predetermined group was 26.3-27.6 sessions and HRVguided was 25.3-26.7 sessions.

Figure 3.3.

Changes in Primary Outcome Metrics



A)VO_2max, **B)** CrossFit Total, **C)** Days at High Intensity, and **D)** Body Fat Percentage. *Significant at 0.05

Discussion

This study tested the effects of HRVguided and predetermined HIFT on health and fitness outcomes within recreationally active participants. Our results support our first hypothesis, as HRVguided prescription resulted in fewer DHI compared to a predetermined prescription. This is demonstrated by the HRVguided group completing 13 of 30 days as modulated, lower intensity training days. Our second hypothesis that HRVguided prescription would elicit greater improvements in fitness outcomes than the predetermined group was not supported by the data. This is evident through lack of significant differences between groups for changes in all primary outcome fitness measures. Collectively, these findings are of interest as they demonstrate HRVguided training results in similar improvements across fitness outcomes while spending fewer training sessions at high intensity compared to a predetermined prescription.

Our finding that HRVguided training did not result in greater changes in aerobic or work capacity than predetermined training in a 9-week HIFT program was similar to previous aerobic exercise investigations where the HRVguided group displayed increases in aerobic capacity with no significant difference between groups (Javaloyes et al., 2019, 2020; Kiviniemi et al., 2007). Additionally, neither a small or moderate effect size was observed between groups as previously reported by V. Vesterinen et al., (2016) and Nuuttila et al., (2017), respectfully. This finding is not atypical as Hautala et al., (2006) has shown that aerobic capacity adaptations are not universal and may be driven by intrinsic factors that predispose individuals to favorable adaptations based on training mode.

We observed no significant differences between groups on improvements in maximal squat, OH press, deadlift, and CrossFit total. The lack of observed group differences is similar to the findings of De Oliveira et al., (2019), on maximal strength in young resistance-trained men

undergoing HRV guided training. However, De Oliveria et al. (2019) used HRV to augment training frequency, while we used HRV to modulate training intensity. Our findings extend upon those of De Oliveira et al., (2019) and suggest that HRV is a practical tool to individualize the prescription of training frequency and intensity. This enhances the practitioner/coach's ability to determine when and how much stress to apply in training.

Our participants showed an increase in overall strength following HIFT participation regardless of group. The finding that HIFT is a valid program structure for improving strength is supported by the findings of Heinrich et al., (2012) and Buckley et al., (2015) in which HIFT participants displayed increases in bench press, back squat, OH press and deadlift 1RM. It is possible that the observed changes in strength were a result of our participants being classified as "novice," or as a result of an effective training paradigm. To determine the cause, future investigations need to apply this intervention across different experience classifications of HIFT participants. These findings demonstrate that HIFT 5 days/week-1 is an effective methodology for improving muscular strength.

Morning rHR significantly decreased for HRVguided and Predetermined groups from pre- to post-test, whereas no significant changes were observed in HRV or the CV of HRV. Our findings differ with those of Kliszczewicz et al., (2016b) who did not observe improvements in rHR after 15-weeks of HIFT, although they also did not find change in HRV. The lack of observed change in HRV may be a function of the nature of HIFT as Schneider et al., (2019) observed a decrease and no change in HRV following a microcycle of strength training and high-intensity interval training, respectively. Although non-significant, changes were found; we did observe a trend for increases in HRV suggesting an increase parasympathetic activity. Previously, it has been demonstrated that increases in parasympathetic activity are associated with improved fitness

characteristics as well as reduced homeostatic perturbations in response to subsequent stressors (Borresen & Lambert, 2008; Kiviniemi et al., 2014; Plews et al., 2013).

Of note we observed similar fitness improvements in both groups despite the HRVguided group spending significantly less time training at high-intensity, 13 less days. This is consistent with the findings of Vesterinen et al., (2016), in which HRVguided recreational endurance runners spent less time training at moderate and high-intensity. Since an individuals' HRV response or ability to maintain homeostatic balance can vary due to training history, exercise modality and exercise intensity, predetermined training prescription may under or over-estimate the necessary recovery time required (De Oliveira et al., 2019; Schmitt et al., 2015; Stanley et al., 2015). The use of HRVguided training prescription may aid practitioners/coaches in optimizing the timing of training stress application.

In addition, participant body composition improved in both of our training groups. This finding contrasts with those of Nuuttila et al., (2017) in which no body weight or fat percent changes were observed after 11 weeks of HRVguided running. The changes we observed may be attributed to the high levels of body fat within our participants > 22% versus < 13% for Nuuttila et al.'s participants. Favorable changes in body composition were also found by Feito et al., (2018b) in both men and women following 16-weeks of HIFT. Like Feito et al. (2018b), our participants were not engaged in physical activity specifically targeting changes in body composition prior to the study thus allowing for a significant change in body composition from pre- to post-test as a result of the training intervention.

A limitation of this study is that HRV measurements were taken by the individual participants and not within a lab setting, which impairs the standardization process. We are unable to say with certainty that all HRV measurements were protocol adherent throughout the study. A

degree of inherent trust must be allotted to participants to strictly adhere to the measurement protocols, and while this increases the external validity of our findings it may have affected our internal validity. We were unable to record and quantify participant internal load (e.g., rHR) or external load (e.g., total training volume) during each training session as done by De Oliveira et al., (2019) to demonstrate the difference in total work completed by both groups. Quantifying the total work completed by participants within each group would provide additional support to the reduced training load completed by the HRVguided group. Participants were instructed to refrain from engaging in any additional exercise outside of the intervention, yet we were unable to ensure these instructions were adhered to throughout the study period. Finally, we were unable to determine the contribution of muscular hypertrophy to the strength gains observed, as muscle cross-sectional area was not assessed.

A key strength of our study is that we were able to demonstrate how a commercially available smartphone application with a low individual cost, can be an effective tool for modulating the individual prescription of exercise intensity. Additionally, we demonstrated high adherence to daily HRV recordings and the exercise protocols by participants. This demonstrates that daily HRV recordings are manageable for participants over 11 weeks. Our participants displayed a high level of HRV compliance (>90%) and training adherence (>80%) over the 11-week intervention. Finally, this is the first study to modulate HIFT training prescription based on individual HRV.

Conclusions

In conclusion, modulating HIFT exercise intensity by individual HRV status resulted in similar fitness improvements as predetermined HIFT for aerobic capacity, strength, cardiovascular adaptations, and body composition despite spending fewer days training at high intensity.

Practically, our findings suggest the use of a rolling average of HRV is an effective tool for modulating daily training intensity with a focus on individual prescription. Coaches and practitioners can use HRV as a tool to effectively individualize exercise prescription for HIFT participation.

Chapter 4 - Association of Heart Rate Variability and Simulated Cycling Time Trial Performance

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Abstract

The aim of this study was to determine if an abnormal HRV status would have negative effects on simulated individual time trial (ITT) performance in recreational cyclists. Recreational male (n = 23, 42.8 ± 8.3 years, 78.0 ± 11.0 kg) and female (n = 2, 37.0 ± 6.8 years, 68.0 ± 4.4 kg) cyclists completed simulated indoor 40-minute ITTs (40TT) over ten weeks. Participants were asked to complete simulated 40TTs under two HRV conditions: HRV normal values and HRV abnormal values. Participants recorded daily morning HRV readings to determine HRV status. Each participant performed all 40TTs on their personal indoor bike trainer and bike without external race simulation (e.g., Zwift). All cycling performance data were recorded on personal bike computers and submitted via a Qualtrics survey. A total of 138 ITTs (Normal = 75; Abnormal = 63) were assessed for relationships between HRV status and performance outcomes using a linear mixed-effects model with Cohen's D for effect sizes (ES). A significant main effect of HRV status was found for peak power (F = 6.61; Normal: 372 ± 29.4 watts; Abnormal: 349 ± 29.60 watts; 380; p = 0.01; ES = 0.20) and peak speed (F = 6.12; Normal = 10.8 ± 0.68 m/s; Abnormal: 10.4 ± 0.68 m/s; p = 0.02; ES = 0.18). No significant main effect or effect sizes exceeding 0.20 were observed for all other performance variables. Daily HRV monitoring provides valuable insight that an individual's peak power and speed may be compromised during cycling performance despite no changes in physiological or psychological indicators of effort. Coaches and cyclists can use morning HRV to inform race strategy ensuring desired performance outcomes, especially for those who rely on high power outputs.

Introduction

The competitive road cycling season includes 90 to 100 competition days, which involve single day "Classic" races and "Tours" lasting one or more weeks (Lucia et al., 2001). Tour races

have three primary competition requirements: flat stages, uphill cycling and individual time trials (ITT) (Lucia et al., 2001). ITTs fall under two categories: “short”, lasting 5 to 10 km, and “long”, lasting 10 to 60 km, during which average power reaches 350W and workloads around 90% of maximal aerobic capacity (Atkinson et al., 2003; Lucía et al., 2007; Padilla et al., 2000). The high physiological demands placed on cyclists’ during ITT make it one of the most physically demanding events in competitive endurance sports (Lucia et al., 2001, 2003).

Maintaining peak physical capacity across the competitive cycling season is essential, and regular monitoring of individual responses to the competitive demands would provide valuable insight into the athlete’s ability to perform. Heart rate variability (HRV) is a popular non-invasive tool for daily monitoring within endurance athletes (Makivic et al., 2013; Plews et al., 2013). HRV is a surrogate index of the autonomic nervous system via the modulation of parasympathetic activity (Camm et al., 1996). Cardiac autonomic regulation is assessed via HRV by measuring time intervals between successive R-R intervals of heart beats, where an increase or decrease R-R interval duration reflects altered autonomic activity (Makivic et al., 2013). To appropriately determine a change in HRV, daily readings should be averaged over a rolling seven-day period with calculated individual smallest worthwhile change windows (SWC), ±0.5 standard deviation) (Kiviniemi et al., 2010; Plews et al., 2013; Vesterinen et al., 2016). Daily HRVs outside of the SWC window are a reliable measure to determine meaningful changes in physiological status or psychological states induced by training or daily stressors (Crawford et al., 2020; Plews et al., 2012). Thus, HRV reflects the individual responses to stress that can provide insight as to when an athlete may require rest or attenuated training loads to optimize athletic performance.

Currently, regular monitoring of HRV has shown promise for the prescription of training intensity/load for cycling and running (Javaloyes et al., 2019; Kiviniemi et al., 2010; Vesterinen

et al., 2016). However, the effects of HRV on same day competitive cycling performance is unclear. Chalencon et al., (2012) observed a positive relationship with swim performance and the high frequency (HF) domain of HRV, representing parasympathetic activity, while a negative relationship occurred with swim performance and the low frequency (LF) domain of HRV, which is influenced by both parasympathetic and sympathetic activity. Alternatively, Coates et al., (2018) found that same day HRV measures were insufficient in predicting alterations to incremental cycling performance. Therefore, the purpose of this investigation was to determine the effects of individual HRV status on performance metrics of ITTs. We hypothesize that a HRV status which falls outside an individual's SWC window on the day of an ITT will result in impaired cycling performance metrics (i.e., total distance, peak and average speed, and peak and average power) compared to days in which HRV status is deemed "normal."

Materials and Methods

Subjects

Twenty-five (23 men, 2 women) trained to well-trained cyclists, classification was determined via Jeukendrup classification system, were recruited for this study (Jeukendrup et al., 2000). All participants performed at least three 60-minute rides per week for at least one year prior to enrollment. Participant inclusion criteria included: ownership of heart rate monitor (e.g. Polar, Garmin), a road bicycle, indoor bike trainer (wheel-on or direct drive train), and a bike computer or smartphone application capable of recording the study performance metrics. Exclusion criteria included: a physical condition or medication which may contraindicate vigorous physical or artificially regulate heart rhythms (i.e., beta blockers). Participant characteristics are presented in Table 4.1. This study was performed in accordance with the Declaration of Helsinki and was

approved by the Kansas State University Institutional Review Board (#10217). All participants provided informed consent prior to study commencement.

Table 4.1.

Participant Characteristics

	Men (n = 23)	**Female (n = 2)**	**Combined (N = 25)**
Age (years)	42.8 ± 8.3	37.0 ± 6.8	42.4 ± 8.17
Weight (kg)	78.0 ± 11.0	68.0 ± 4.4	77.5 ± 10.6

Design

This study used a 12 week quasi-experimental repeated-measures design to test the effects of HRV status on simulated 40-minute ITT (40TT) performance metrics (e.g., distance; speed, and power). Participants were recruited from around the world via social media marketing (e.g., Facebook, Instagram). Once participants were screened and enrolled, they completed 14 days of resting HRV measurements, which served as a baseline. Following the baseline period, participants continued recording morning HRV readings and began performing the simulated 40TTs. Participants were asked to perform a total of six 40TTs: three trials after a normal HRV status measure and three trials after an abnormal HRV status measure. At least 48 hours separated each 40TTs. Upon completion of each 40TT, participants submitted performance metrics to the research team. Throughout the study participants were asked to not alter training or start a new training regimen.

Heart Rate Variability (HRV)

Morning HRV was measured daily throughout the study. All participants were instructed to measure their pulse-rate intervals upon waking and after emptying their urinary bladder. HRV was measured in a supine position for 1-minute; participants were instructed to lie still and not perform any further activity once the recording was started (Plews et al., 2017). The HRV measurements

were captured with the commercially available smartphone application HRV4Training (https://www.hrv4training.com/). The HRV4Training software uses photoplethysmography to determine the variability in successive R-R intervals during continuous heart rate data (Plews et al., 2017). The HRV4Training application has a built-in methodology for signal filtering, processing, interpolation, artifact correction, and R-R peak detection which can be found in the reference for the application development (Plews et al., 2017). For day-to-day monitoring of individual recovery (i.e., sympathovagal balance) HRV was measured as the root mean squared of successive differences (RMSSD) and due to its lack of normality was transformed using the natural logarithm (LnRMSSD). Then, LnRMSSD was multiplied by two so that LnRMSSD could be viewed on a scale of approximately one to ten for ease of participant interpretation. A seven-day rolling average of an individual's HRV was calculated and used throughout the study to determine changes in vagal activity (Williams et al., 2017). The HRV4Training application calculates individual SWC windows based on seven-day rolling average HRV. A day of HRV reading outside of the individual SWC was deemed as an abnormal HRV, while an HRV within the individual SWC was deemed as a normal HRV.

40-minute Simulated Individual Time Trial (40TT)

Cyclists performed six 40-minute all-out ITTs indoors on their own bike and cycling trainer without the use of virtual cycling programs (i.e., Zwift, Rouvy). Participants were asked to record environmental conditions (i.e., temperature, humidity), and were asked to keep them consistent on each 40TT. During all 40TTs, participants were instructed to wear a heart monitoring device (e.g., Polar, Garmin). Participants performed a 10-minute warm-up at a constant work rate of 50 watts prior to each 40TT. Participants immediately initiated the 40TT after the warm-up and were allowed to change their gear ratio and pedal frequency and drink water ad libitum. Each 40TT was

followed by a 10-minute cool-down. Average and peak power, average, and peak heart rate (HR), average and peak speed and total distance were recorded for each 40TT via cycling computer or application (e.g., Polar, Garmin, Strava and Wahoo). Additionally, participants recorded their rate of perceived exertion (RPE) upon completion of the 40TT. All data was submitted to the research team via a Qualtrics (Provo, UT) survey.

Statistical Analysis

Data were analyzed using the R statistical computing environment and language (R Core Team, 2020) via the Jamovi graphical user interface (The Jamovi Project, 2020). Descriptive statistics were calculated, and all dependent variable data were checked for normality prior to inference testing. Relationships between the fixed effect (i.e., HRV status) and performance outcomes (i.e., average and peak HR, average and peak power, average and peak speed, RPE, and distance) data were assessed using linear mixed-effects models via the *GAMLj: General analysis for linear models* Jamovi module (Gallucci, 2019). Individual participants identifiers were input as the random factors within these models and a correlation matrix was used to determine covariates. When appropriate, covariates used for each respective performance outcome are noted below. Age was included as a covariate for peak speed, peak power, and RPE. Weight was included as a covariate for average power. Age and weight were included as covariates for max HR and average HR. An alpha level of 0.05 was used for all statistical inferences and post hoc comparisons were adjusted using the Bonferroni correction. Cohen's D was used to estimate observed effect sizes (ES) between HRV statuses. ESs were classified as small (0.2), medium (0.5), and large (0.8) (Cohen, 1988). Individual SWC windows, standard deviation * 0.2, were calculated for performance metrics during normal HRV 40TTs. Performance metrics during abnormal HRV 40TTs were compared against individual SWC windows to determine whether individual

performances were altered beyond day-to-day variability. All data are reported as mean ± standard deviation.

Results

A total of 138 ITTs were analyzed (Normal = 75; Abnormal = 63). Differences in peak power and peak speed are shown in Figure 4.1. A significant main effect of HRV status was observed for peak power and peak speed No significant main effects were observed for total distance, average speed, average power, peak HR, average HR and RPE. All outcome variable results are presented in Table 4.2. The number of individuals with an altered 40TT performance when HRV was abnormal is displayed in Table 4.3. 40TTs with an abnormal HRV resulted in either in increased or diminished peak watts for 70% of participants, peak speed for 55% of participants, and average speed for 58% of participants.

Table 4.2.

Time Trial Outcomes by HRV Status

	Normal HRV Status		Abnormal HRV Status		Between Groups		
	Mean ± SD	95% CI	Mean ± SD	95% CI	*p*-value	F	ES
Peak power (W)	372 ± 121.5	341, 403	349 ± 105.9	318, 380	0.01	6.61	0.20
Average power (W)	236 ± 45.58	220, 252	234 ± 36.83	218, 250	0.45	0.59	0.05
Peak speed (m/s)	10.8 ± 1.2	10.1, 11.5	10.4 ± 1.2	9.7, 11.1	0.02	6.12	0.33
Average speed (m/s)	6.2 ± 0.49	5.6, 6.7	6.0 ± 0.49	5.6, 6.6	0.39	0.74	0.05
Total Distance (km)	22.2 ± 2.79	20.3, 24.0	20.3, 24.0	20.0, 23.7	0.17	1.95	0.17
Peak HR (bpm)	171 ± 17.59	167, 176	171 ± 15.13	167, 176	0.79	0.07	0.00
Average HR (bpm)	155 ± 17.13	150, 161	156 ± 17.13	151, 161	0.83	0.05	0.06
Rating of perceived exertion	8.97 ± 1.24	7.59, 8.56	8.05 ± 1.24	7.56, 8.54	0.83	0.05	0.02

Figure 4.1.

Comparison of Performance Outcomes; Peak Watts and Peak Speed

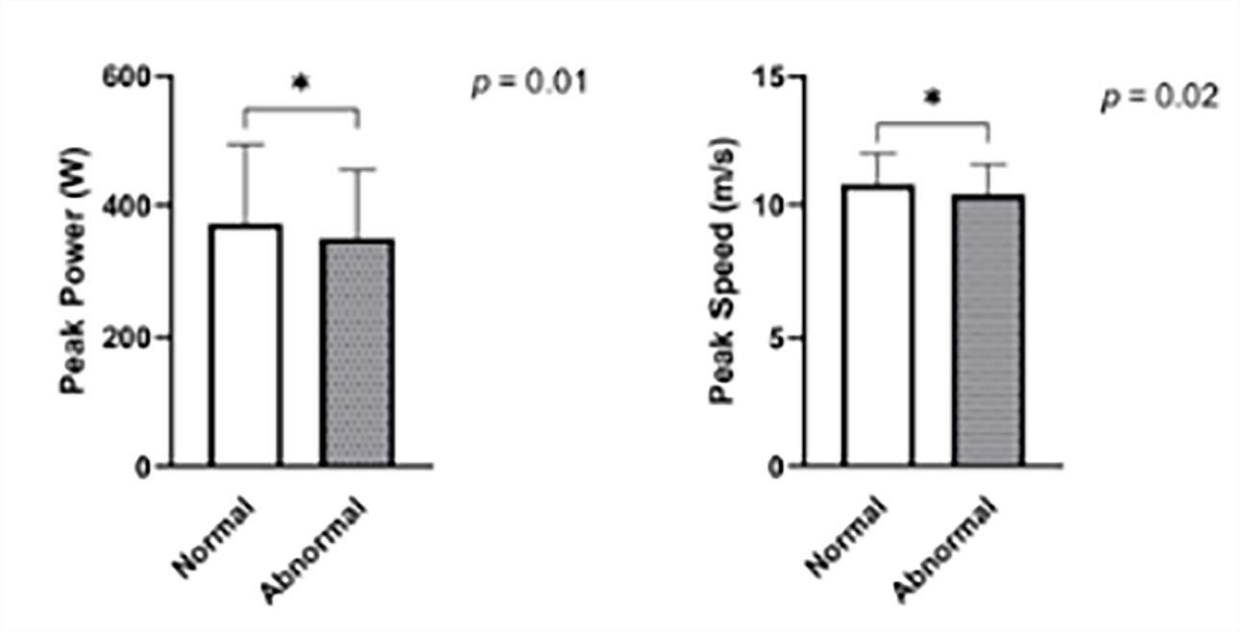

Table 4.3.

Individuals with a Performance Outside of Their SWC Window when HRV was Altered

Performance Metric	Individuals affected
Total Distance (km)	8/22 (36%)
Peak speed (m/s)	12/22 (55%)
Average speed (m/s)	7/22 (32%)
Peak watts (W)	14/20 (70%)
Average watts (W)	11/19 (58%)

Discussion

The purpose of this investigation was to determine the effects of HRV status on physiologic and performance metrics of simulated ITTs in trained to well-trained cyclists. Importantly, these

data show that abnormal HRV status impairs an individual's ability to produce peak power and peak speed potentially resulting differences in distance covered during a simulated ITT. However, no effects were observed on physiological (i.e., HR) or psychological (i.e., RPE) indicators of effort during ITT.

To the best of our knowledge, this is the first study to investigate the effects of same day HRV status on simulated cycling performance. Our findings are in agreement with previous reports demonstrating superior performance outcomes corresponding with favorable (i.e., normal) HRV measures (Atlaoui et al., 2007; Chalencon et al., 2012). Previously, top level swimmers demonstrated a strong, positive relationship between performance (i.e., percent of best previous performance) and high frequency power – an index of parasympathetic activity (Atlaoui et al., 2007; Chalencon et al., 2012). This finding supports the notion that increased parasympathetic activity occurs during a state of recovery and an increased fitness level (Plews et al., 2013). Additionally, LnRMSSD is related to maximal aerobic running speed during both 10 km (Buchheit et al., 2010), and 21 km performances (Boullosa et al., 2021). Collectively, these findings further support the notion that even temporary shifts in ANS activity play a significant role in performance capacity.

Interestingly, we did not observe differences in physiological or psychological indicators of exercise intensity despite the increased peak power and speed during normal HRV. Our findings corroborate those of Coates et al. (2018) in which resting HRV was not associated with reductions in average and max HR during maximal incremental cycling tests. Additionally, we saw no differences in RPE between normal and abnormal HRV status during the 40TT, similar to reports of female cyclists competing on the Tour de France circuit (Barrero et al., 2019). Our findings suggest that cyclists more reliant on high power outputs (e.g., criterium racers or track cyclists)

may have greater decrements in race performance than endurance cyclists (e.g., stage and triathletes) when HRV is altered.

A key strength of this study is the high external validity. This was one of the first studies to directly compare HRV and same day performance for participants training and performing in free-living conditions. Thus, our study is the first to reflect the current state of remote/distance coaching of athletes. Additionally, participants completed multiple simulated 40TTs within each HRV condition. This study presents three main limitations. First, we were unable to control each participant's training load and prescription. Second, as we were not able to predict when an HRV would fall outside a SWC, we could not standardize the time between 40TTs, nor the time of day that each 40TT was performed. Finally, with all 40TTs being performed remotely, we were unable to perform additional measurements that would provide insights into the mechanistic changes occurring during the 40TTs.

This study demonstrated two important findings. First, an abnormal HRV status resulted in impairments in peak power and peak speed which may reduce distance covered during simulated 40TTs performance metrics, which is critical since distance is an essential determinant of overall cycling performance. Second, intra-performance markers of physiological and psychological intensity were not sensitive indicators of a decreased performance. Future research with a larger sample and greater internal validity control is needed to determine the mechanisms for the reduced simulated ITT performance.

Practical Applications

Coaches and sports scientists who aim to optimize cycling performance need to gain insight into the athlete's physical capacity on race day. Daily monitoring of HRV seems to provide valuable information regarding whether an individual's peak power and speed may be

compromised the day of a critical ITT performance. Coaches and cyclists may choose to use morning HRV to inform race strategy (i.e., domestique selection). Additionally, power-based cycling events (e.g., criterium and track cyclists) may experience greater performance changes due to altered HRV compared to their endurance-based counterparts.

Chapter 5 - Conclusion

This dissertation and the body of work it represents adds valuable information for practitioners, coaches, and researchers to enhance exercise prescription though the use of daily HRV readings. The overall hypothesis of this work was that daily HRV is an effective tool for monitoring individual physiological responses to exercise training and therefore the utilization of daily HRV can enhance the outcomes of exercise prescription. In the first study, we found a negative relationship exist between daily HRV and the testosterone-to-cortisol ratio, during regular participation of high-intensity functional training, a program that went beyond a purely aerobic or single exercise modality, as contemporary exercise prescription utilizes both aerobic and resistance training. Additionally, we showed that daily HRV has excellent sensitivity (95%), but poor specificity for detecting meaningful changes in the T:C ratio (Chapter 2). These findings provide further evidence of HRV's ability to align with previous methods of monitoring training responses with increased practicality. To further test the capacity of daily HRV readings, it was essential to design an intervention.

Our second study (Chapter 3) compared the effects of HRVguided to predetermined HIFT on cardiovascular function, body composition, performance. For this study, the HRVguided training group had their daily exercise intensity prescribed based upon the HRV measurements. In this study we found that resting heart rate, lean mass, fat mass, overall strength, and work capacity significantly improved for both groups, with no significant between group differences. However, the HRVguided group spent significantly fewer days training at high intensity than the predetermined group. These findings demonstrate that HRV is effective for the prescription of exercise intensity beyond aerobic or single modality training, while also showing that HIFT can be an effective training modality without performing at high intensity during every exercise

session. Despite these promising findings it was still unclear if changes in HRV status would limit exercise performance.

In our final investigation (Chapter 4) we examined the effects of individual HRV status on performance metrics of a simulated cycling time trial. This was one of the first studies to examine this relationship in free living conditions and without the additional participant stress of an exercise intervention. The novel findings from this investigation were that when HRV was altered participants displayed a reduced peak power, peak speed and total distance covered, however, they did not experience any changes in metrics of physiological or psychological effort. This interesting finding suggests cycling coaches may use morning HRV to inform race strategy (i.e., domestique selection) during tour races and that power-based cycling events (e.g., criterium and track cycling) may experiencer greater changes in performance than their endurance-based counterparts. Despite these novel findings, we did not directly examine any underlying physiological mechanisms that may have resulted in the compromised performance metrics. It is well understood that a variety of factors outside of exercise training (e.g., physiology, environment, psychology) play an influential role on HRV, these factors were not accounted for within our study designs. Future investigations with a controlled study design may benefit and provide additional insight by accounting for these influences.

In conclusion, this body of work provides further support for the use of HRV to guide individualized exercise prescription. Standardized or predetermined exercise prescription fails to account for the individual adaptations that occur during an exercise training program and an individualized approach is necessary to optimize outcomes. An individualized approach to exercise prescription would benefit from the creation and implementation of ANS and hormonal profiles to aid in the determination of exercise training intensity. Additionally, daily monitoring of

HRV provides an effective, time efficient, and non-invasive method for monitoring individual responses to exercise training beyond aerobic or single modality training. Alterations in HRV indicate that an individual may have compromised recovery or does not have the ability to perform at the maximum of their abilities. Future investigations on the mechanisms resulting in the compromised ability to perform and understanding the role of an individual's psychological state would provide greater insight into individual responses to the increased stress of exercise training and performance.

Chapter 6 - References

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Appendix

Figure A.1.

Details of the High-Intensity Functional Training Intervention

Day	Structure	Structured Daily Workout
1	M	Two-mile Run (no time cap)
2	GW	[8 Push Press (135/95 lbs.) + 8 Pull-Ups] x 5 rounds for time
3	MGW	[12 Goblet Squats (45/25 lbs.) + 12 Burpees + 24 Calorie Row] AMRAP in 10 min
4	MG	[400-meter Run + 25 Box Jumps (18/12‘‘)] x 3 rounds for time
5	W	Deadlift 5-5-5-5-5 working up to target 85% of 1RM
6	G	Kipping Pull-Up practice for 20 min
7	WM	[10 Thrusters (135/95 lbs.) + 100 Double Unders] x 4 rounds for time
8	GWM	[6 Handstand Push-Ups + 12 Deadlifts (185/135 lbs.) + 500-meter Row] AMRAP in 12 min
9	GW	[15 Ring Rows + 20 Wall Balls (20/14 lbs.)] x 4 rounds for time
10	M	8k meter Partner Row (no time cap)
11	W	Front Squat 1-1-1-1-1-1-1-1-1-1 working up to target a 1RM
12	MG	[400-meter Run + 20 Push-Ups] x 5 rounds for time
13	WMG	[5 Cleans (135/95 lbs.) + 10 Pull-Ups + 15 Double Unders] AMRAP in 15 min
14	WM	[10/20 – 8/16 – 6/12 – 4/8 – 2/4 repetitions of Power Clean/Calorie Row] for time
15	G	Handstand Push-Up Practive for 20 min
16	W	Squat 3-3-3-3-3-3-3 working up to target 90% 1RM
17	MG	[800-meter Run + 25 Sit-Ups] x 3 rounds for time
18	MGW	[50 Double Unders + 5 Box Jumps (18/12‘‘) + 15 Ball Slams (20/14 lbs.)] AMRAP in 15 min
19	GW	[6 Strict Pull-Ups + 6 Front Squats (50% Squat 1RM)] x 4 rounds for time
20	M	Two-mile Run (no time cap)
21	M	Tabata Double Unders x 2
22	GW	[Maximum repetitions Handstand Push-Ups + 6 Deadlifts (75% 1RM)] x 5 rounds for time
23	GWM	[20 Sit-Ups + 16 Dumbbell Clean and Jerk (45/20 lbs.)
24	WM	[30 Kettlebell Swings (45/20 lbs.) + 400-meter Run] x 5 rounds for time
25	G	Strict Pull-Up Practice (Loaded) for 25 min
26	G	Muscle Up Practice for 25 min
27	WM	[6 Squats (50% 1RM) + 50 Double Unders] x 4 rounds for time
28	WMG	[12 Goblet Squats (45/25 lbs.) + 12 Burpees + 24 Calorie Row] AMRAP in 10 min
29	MG	[400-meter Run + 10 Handstand Push-Ups] x 5 rounds for time
30	W	Clean 1-1-1-1-1-1-1-1-1-1 working up to target 1RM

Note. M = monostructural (i.e., a single cardiovascular exercise modality) exercise, G = gymnastics exercise, W = weightlifting exercise, and AMRAP = “as many rounds as possible.” *Daily workouts were scaled to match individual capabilities on an as needed basis. All scaling options were in accordance with outlined CrossFit scaling practices Glassman (2016) (p. 75). Table is adapted from Crawford et al (2019)