Review Article
Volume 15:02, 2024

Journal of Health & Medical Informatics

ISSN: 2157-7420

Open Access

Exercise and Real-world Training Using Pulse Rate Variability: A Systematic Review of Wearable Photoplethysmography Technology and Real-world Interventions

Michael R. Coggins*

Replicate International Inc., 161 E. 55th St., New York, NY 10022, USA

Abstract

Background/Rationale: Photoplethysmography (PPG) may enable large-scale, accurate and cost-effective measurement of Pulse Rate Variability (PRV) as a surrogate for Heart Rate Variability (HRV) to inform real-world training of athletes. A significant body of research has investigated HRV as a non-invasive composite measure of cardio-autonomic function with application to exercise interventions and training protocols for athletes and athletics. However, the rapidity of commercialization of PPG-based wearables raises the question of what clinical research exists to enable real-world usage analogous to HRV-based wearables. PPG from wearable devices is a fundamentally different technology than the Electrocardiogram (ECG). Similarly, HRV and distally measured PRV may represent different underlying physiological processes or time courses.

Aim: Perform a literature search of all exercise, athletic training, and athletic performance research using commercial wearable devices with PPG.

Methods/Conclusions: The major gap in understanding of PRV measurement is how to use results to inform real-world training protocols and interventions. Few papers were found evaluating PRV measured by PPG technology for athletes, exercise, or training recommendations. Over half of the literature search findings are devoted to custom devices/software or would be difficult to replicate for field usage. Only a few studies examined PRV over time periods necessary for training adaptations and no studies were identified that tested varied exercise protocol micro/macro-cycles. We recommend both more clinical studies of PRV from PPG technology to stratify underlying physiological mechanisms of value for athletics, and real-world studies to inform progressive exercise training methods and benefits/limitations of PRV outside of the clinical lab.

Keywords: Wearable devices • Photoplethysmography • PPG • PPG technology • Athletes • Training • Pulse rate variability • prv • Heart rate variability • Hrv • Exercise • Real-world data

Introduction

Training of athletes of all experience levels has a rich history of using non-invasive quantitative measurements of human physiology to direct exercise programs, inform recovery programs, and achieve performance milestones. Traditionally, the technology and methodology for these quantitative analytics has been developed first, or co-operatively, through clinical lab testing, followed by adoption and adaptation for usage by coaches, athletes, and practitioners. Here I compare and contrast findings with these devices operating in lab conditions versus real world conditions.

Academic physiology labs began experimenting with non-invasive measurement of athlete Heart Rates (HRs) to indirectly measure physiological effects of different exercise modalities in the 1950s [1]. These lab tests enabled HR measurement to move from the clinic into the real-world training environment and inform other indirect metrics in the 1970-1980s. One example metric, VO_2max, could be correlated with HR to enable real-world usage of useful metabolic training methods [2,3].

Concurrently, medical clinicians began experimenting with Electrocardiogram (ECG) measured HR and Heart Rate Variability (HRV) in the 1960-70s [4]. HRV measurement is a non-invasive, complex and composite measurement of athlete physiological response to different modes, intensities, and durations of exercise and exercise programs [5]. In addition to athletic studies, HRV has been analyzed in clinical studies of mental load and cognitive tasks [6,7], prediction of cardiac mortality [8,9], and modulation of the autonomic system amongst other states and syndromes [10,11]. When technology evolved to portable, low-cost single-lead ECG systems (eg. PolarTec), HRV measurement moved out of the lab and into further innovation in the field through real-world athletic testing in the 2000s [12].

Photoplethysmography (PPG) used for HR-related measurements of cardio-pulmonary-autonomic function was theorized as early as 1937 [13]. The technological advancement of low-power and inexpensive Light-Emitting Diodes (LEDs) by 2001 led to the development of compatible devices [14]. At present, technology for reflectance PPG is characterized by the usage of one or more LEDs and a light reflectance sensor to non-invasively probe changes in reflectance of light from underlying tissues as a proxy for increasing/decreasing density of blood in arterial vasculature at the fingertip, ring, earlobe, wrist, or proximal forearm near the elbow [15]. PPG measures light reflection changes due to density changes of vascular light-reflecting compounds presumably directly related to mechanical expansion and contraction of blood volume and is influenced by heart rate [16], resting blood volume [17], Respiratory Sinus Arrhythmia (RSA) [18] and likely other physiological properties [19,20].

Similar to ECG-based technology [21], PPG-based technology moved from initial lab experiments to real-world usage with the rapid commercialization of wearable devices (eg. Nike Fuel Band, Garmin, FitBit), including smartphones, containing PPG sensors. However, the rapidity with which PPG technology and consequent recommendations was embraced by commercial manufacturers, and the enormous potential real-world usage of PPG sensors to inform exercise and recovery decisions, raises a question as to how much clinical testing has been performed using PPG during exercise or recovery, and for training or performance concerns. These questions form the basis of this review.

***Address for Correspondence:** Michael R. Coggins, Replicate International Inc., 161 E. 55th St., New York, NY 10022, USA, Tel: +1 9177155967, E-mail: mrc@replicateinternational.com*

Received: 26 February, 2024, Manuscript No. jhmi-24-128284; **Editor Assigned:** 27 February, 2024, PreQC No. P-128284; **Reviewed:** 13 March, 2024, QC No. Q-128284; **Revised:** 19 March, 2024, Manuscript No. R-128284; **Published:** 27 March, 2024, DOI: 10.37421/2157-7420.2024.15.516

The purpose for this literature review is to compile updated information from studies that used wearable devices containing Photoplethysmography (PPG) technology intended for athletes, athletics, and performance training in the real-world setting. Analogous to the purpose of Real World Data (RWD) or Real World Evidence (RWE) trials [22], as continuing, useful supplements to lab-based, controlled-environment, clinical trials for understanding health decisions, this review is meant to better understand the usage of PPG-based wearable devices for athletics or training continuing after and outside of the lab environment. For data that focus more on lab-based non-commercial PPG devices in comparison to ECG, or focused on non-exercise conditions, please refer to the excellent reviews by, El-Amrawy F and Nounou MI [23], and Schäfer A and Vagedes J [24].

Consistent with our purpose, and the challenges of RWD/RWE experiments, we chose to focus on the type and location of PPG-hardware/software technology utilized, and the analytic techniques and experimental methods employed by researchers, rather than focus on meta-data analysis or results (for meta-data analyses, see Georgiou K, et al. [25]). To better identify the continuing usage of wearable PPG technology for athletics, training and performance, our search and presentation is meant to identify areas of opportunity for experiments and data collection for performance training during real-world usage of wearable devices with PPG technology.

Methods

Scope

The scope for this literature review is restricted to primary experimental data from PPG technology used to monitor Pulse Rate Variability (PRV) as an input to training and exercise decisions for athletes and athletics. This review only considers portable PPG devices as acceptable technology and requires the experiments to include some form of exercise or movement designed to be significantly different in some physiologically meaningful measure from a resting state. We do allow the definition of athlete and athletics to be broad in order to encompass any subject, of any age, gender, or background as a potential athlete, as long as there is some condition used by experimenters intended to replicate athletic-like endeavors by the subjects.

Search

Searches of online and hardcover manuscripts consisted of two epochs: first, beginning in April, 2019 and continued through January, 2020, with a second epoch of Jan 1, 2024 continuing through Feb 2, 2024. Online searches were performed using PubMed, MEDLINE and the New York University (NYU) Search Portal. Physical searches of uncatalogued or missing manuscripts utilized the NYU Library system. Search terms included the following as an initial probe of the literature:

- ((("ppg" or "photoplethysmography") AND ("exercise" or "sport" or "sports" or "athletics" or "athletic") AND ("wearable" or "worn") and (hrv or "heart rate variability" or "PRV" or "pulse rate variability")))
    - 192 records found
- ((((("wearable" or "wristworn" or "wrist-worn" or "watch technology" or "ppg")) AND ("hrv" or "heart rate variability")) AND ("time domain" or "time-domain" or "frequency domain" or "frequency-domain")) AND ("fft" or "hf/lf" or "lf/hf" or "sdnn" or "rmssd"))
    - 19 records found
- ((("ppg" or "photoplethysmography")) AND ("wrist-worn" or "wrist worn" or "wrist")) AND ("exercise" or "sport" or "sports" or "athletics" or "athletic")
    - 33 records found

Inclusion and exclusion criteria

Initial pruning of our search was based on duplicate data. If manuscripts contained the same data or utilized a previously created/used public dataset, the original paper with the most data using identical subjects, methods, etc. or the most recent paper was included if:

a) The paper(s) directly used human subjects, and

b) Contained the most data from the human subject sample population.

Review papers were utilized to find additional primary data not discovered by our search terms. However, review papers are not included in the results for discussing technology, experimental methods, or analytic techniques. Follow-on papers were excluded. Secondary pruning consisted of removing single subject case studies, studies involving no movement reasonably described as exercise (e.g. sleep studies) and manuscripts not written in the English language.

Results

Twenty-seven published papers were discovered utilizing wearable devices containing Photoplethysmography (PPG) as data collection technology for physiological adaptations during or after exercise. Significantly more primary literature has been produced using Electrocardiographic technology (ECG/EKG and variations) to understand subject responses during or post-exercise; for reviews please see Plews DJ, et al. [26].

Therefore, instead of continued pruning and removing papers for consideration, I chose to categorize the manuscripts according to two hardware/methodological criteria:

1. PPG-based technology intended for lab usage (non-commercial usage or custom devices) *vs*. PPG-based technology intended for real-world usage (commercial or field usage)
2. Smartphone-based PPG measurement *vs*. Arm-wearable device PPG measurement

The first categorization of papers using wearable devices containing Photoplethysmography (PPG) and exercise, was based on whether the wearable device could be used for data collection, analysis, and recommendations outside of the lab environment by an athlete. Several, early papers utilized fingertip-based PPG, custom-built PPG devices, or products difficult to obtain in the commercial environment (eg. PulseOn) that would not be expected to be used by athletes outside of a lab environment. These papers are presented in (Table 1).

Our second categorization of papers was based on whether the data were recorded from a smartphone device or an arm-wearable, commercial product. The location where measurement is taken, expected style of usage, physical sensors integrated in the device, and software data pre-processing could be expected to be different between smartphone sensors and arm-wearable devices. Therefore, we categorized papers using smartphones to record data (Table 2) and papers using arm-wearable PPG technology (Table 3) as distinct. Our search returned 11 papers using lab-based, or non-commercial PPG-based systems (Table 1), 4 papers using smartphone-based PPG hardware/software (Table 2) and 12 papers using arm-wearable PPG-based commercial devices (Table 3).

Studies utilizing non-commercial PPG-based systems generally consisted of either finger-mounted PPG-based devices using infrared, red, or green wavelengths [27-29] or wrist-mounted PPG-based devices [30,31]. The papers we located generally used healthy subjects [18-20,32-34] although two notable papers looked at subjects with cardiovascular disease, and hypertension [29]. All the studies were observational in nature with one exception using changing ambient temperature [19]. Experiments focused on comparing PPG-based device data with ECG data as a measure of accuracy and all but one used treadmill-based walking/jogging/running to evaluate exercise effects on Heart Rate (HR). Unfortunately, none of these studies evaluated PRV.

Smartphone-based exercise data collected from PPG was only recorded in four papers to my knowledge. In these papers, iOS compliant phones were used in a manner where the camera acted as the PPG sensor in contact with the subject's fingertip [35,36]. In one early paper the subjects tested

Table 1. Papers containing experiments using Photoplethysmography (PPG) in the lab-setting where the technology/hardware is non-commercially available.

Study	PPG Technology (Hardware)	Data Collection/Pre-processing	Subjects	Experiment Design	Analytic Measurements
Drinnan MJ, et al.	PPG recorded simultaneously with ECG from subject. PPG recorded from fingertip, while ECG recorded from chest.	ECG and PPG sampled with 2 kHz. Amplifiers of 0.05-100 Hz used for ECG and 0.5-30 Hz for PPG.	Healthy subjects (N=15, males=11), of middle age (38.8 ± 9.3 years old). 10 subjects were available after 1 year for follow-up	Observational, single study arm. Subjects were supine and recordings were performed for 5 minutes. Breathing was set to be 6 breaths/minute.	First minute of recording was ignored. Remaining four minutes were analyzed as 1 minute epochs. For each 1 minute epoch, maximum change in RR/PTT interval calculated and SD of changes for all intervals calculated.
Selvaraj N, et al.	Lead II ECG and finger-tip PPG (TSD200, BIOPAC Systems). Lead II ECG in standard position; finger-tip PPG was placed on middle right finger	MP 150 (BIOPAC Systems) with AcqKnowledge 3.8.2 software was used to simultaneously acquire ECG and PPG signals at 1 kHz.	Healthy subjects (N=10, 9 males)	Observational, single study arm. 5 min recordings in supine position recorded after 15 minutes of rest.	RR tachograms were recorded as basis of data analysis. Time domain measures (mean NN interval, mean HR, SDNN, rMSSD, SDSD, NN50, pNN50), frequency domain measures (total band power, VLF, LF, HF, LF/HF ratio) and non-linear measures (Poincare plot SD1, SD2 and SD1/SD2).
Gil, et al.	PPG recorded by Biopac PPG100C, while ECG recorded from Biopac ECG100C. PPG was recorded from the index finger, while ECG was recorded from the standard lead.	Software was acquired simultaneously using MP 150 (BIOPAC Systems), a computer-based data acquisition system with the software AcqKnowledgeR 3.9.0. PPG sampled at 250 Hz, while ECG at 1 kHz.	Healthy subjects (N=17, males=11), young in age (28.5 ± 2.5 years old), with low BP (113.6 ± 16 mmHg systolic, 62.8 ± 14 mmHg diastolic)	Observational, single study arm. Subjects underwent recordings during stationary baseline, followed by non-stationary head tilt followed by another stationary rest period.	Time domain measurements: NN, SDNN, pNN50, rMSSD. Frequency domain measurements: VLF, LF (0.04-0.15 Hz), HF (0.15-0.4 Hz) and LF/HF in normalized units.
Zhang Z	Custom LED in pulse oximeter used for PPG. Single-channel ECG used as reference. PPG recorded from wrist, ECG lead located on chest.	Signals were sampled at 125 Hz and transmitted through Bluetooth.	Healthy subjects (N=10, all male)	Observational, single study arm. Subjects performed a series of walking to running exercises on a treadmill.	Authors expected a reported, estimated HR every 2 s. ECG measurements were converted to heart rates for comparison with PPG
Shah MH, et al.	Optical sensor. PPG located on index finger (infra-red wavelength)	Easy Pulse Analyzer and CoolTerm were used for wave shapes from a custom Arduino processing board. Kubios HRV software used to analyze PPG. Sampling of 200 Hz implied.	Healthy subjects (N=4)	Observational, single study arm. Subjects performed sitting, standing, laying and jogging.	Time domain measurements used: LF (0.04-0.15 Hz), HF (0.15-0.4 Hz), Total power, LF/HF. Both FFT and autoregression used to analyze time domain.
Zhang Z and Liu B	Custom LED in pulse oximeter used for PPG. Single-channel ECG used as reference. PPG recorded from wrist, ECG lead located on chest.	Signals were sampled at 125 Hz and transmitted through Bluetooth.	Healthy subjects (N=12, all male) aged 18-35.	Observational, single study arm. Subjects performed a series of walking to running exercises on a treadmill.	ECG measurements were converted to heart rates (bpm) for comparison with PPG.
Ahmadi AK, et al.	Custom LED in pulse oximeter used for PPG. Single-channel ECG used as reference. PPG recorded from wrist, ECG lead location not specified.	Signals were sampled at 125 Hz.	Healthy subjects (N=12, all male).	Observational, single study arm. Subjects performed "fast running".	ECG measurements were converted to heart rates (bpm) for comparison with PPG.
Pinheiro N, et al.	PPG and ECG recorded from HP-CMS monitor with data logger functionality. PPG was attached to tip of index finger	PPG signal was recorded at 125 Hz (ECG at 500 Hz). 180 s sliding window was used for to relay data.	Both healthy subjects (N=33), aged 29.7 ± 8.5 with BMI 24.5 ± 2.41 kg/m^2, and subjects with cardiovascular disease (CVD, N=35), aged 59 ± 17 years, with BMI 25.4 ± 10 kg/m^2.	Observational, two study arms. Study arm 1 was healthy subjects studied at rest or after moderate treadmill exercise. Study arm 2 was CVD patients.	Time domain measurements included: mean, SDNN, SDSD, rMSSD, NN50 and pNN50. Frequency domain features included: normalized VLF, LF, HF bands and aLF/aHF.
Shin H	PPG and ECG recorded simultaneously from undisclosed device and undisclosed location on the body (while seated).	Data collected simultaneously. Sampling rates, pre- and post-processing not disclosed.	Healthy subjects (N=27, males=17), young in age (mean=20.8 ± 1 years old), with average BMI (22 ± 2.4 kg/m^2)	Observational, single study arm. Subjects were seated in three different ambient temperature rooms (unclear if subjects moved rooms during single recording period).	Time domain measurements included: AVNN, NN50, pNN50, SDNN, SDSD, rMSSD. Frequency domain analysis included: LF, HF, VLF, nHF, nLF, LF/HF
Morelli D, et al.	Wrist-worn PPG recorded simultaneously with ECG (Polar H7)	Outlier values removed before processing HR, HRV calculations. Accelerometry used for removal of motion artifacts.	Healthy subjects (n=6, all male) of early middle age (23 ± 6 years).	Observational, single study arm. Subjects did not control for breathing, but for types of movement and usage of additional sensor (accelerometer) to process signal differences due to motion	Subjects sat still for 5 min, followed by stair climbing for 5 min, followed by sitting still for 10 min followed by 10 minutes of sitting with normal activity

Lan KC, et al.	Ring-worn. PPG worn around last (5th) finger, with unit worn around wrist.	Wrist unit enabled sending of data over 24 hr *via* ZigBee radio standard. 8-bit processing of HR (sampled at 64 Hz) used. 5 beat HR sliding window used to calculate HR as an average of the 5 most recently generated HRs. Data collected 11 pm-5 am	Training data (for MILL algorithm) had combination of healthy (N=15) and hypertensive (N=15) subjects. The testing group had healthy (N=4) and hypertensive (N=9) subjects.	Observational, single study arm. Additionally, an algorithm was fed data from a second group of subjects to test for forecasting ability to discriminate hypertensive from healthy subjects.	Time domain measurements: SDNN, Mean RR, and rMSSD. Frequency domain measurements: normalized LF (0.04-0.15 Hz), HF (0.15-0.4 Hz) and LF/HF.

Table 2. Papers containing experiments using Photoplethysmography (PPG) from a commercially available smartphone.

Study	PPG Technology (Hardware)	Data Processing	Subjects	Experimental Design	Analytic Measurements
Altini M and Amft	Smartphone data was collected from commercial program "HRV4Training. com"	1-min recordings of finger over smartphone camera were used. Software used 30 Hz sampling followed by band pass filtering and cubic spline interpolation. Resulting data were then up-filtered for HRV analysis	N=797 users of "HRV4Training. com" app users (mean age 39.8 ± 10.6 years; n=123 female).	Observational, longitudinal. Users were grouped according to gender, age and self-reported exercise intensity (rest/low vs. average to high)	HR and HRV (PRV) were analyzed. HRV was measured according to lnRMSSD. Standing versus sitting or lying down was not specified.
Lee EU, et al.	ECG and PPG tested simultaneously from Holter monitor (ECG) and iPhone 4S camera (PPG). Holter monitor attached to chest, PPG recorded from fingertip	HR from smartphone PPG was collected by a proprietary software program. ECG data collected with MARS program (GE Healthcare).	Subjects with heart disease (N=16, all male), generally middle age to older (44-70 years old)	Observational, with single study arm. Subjects measured at rest, at Bruce protocol stage I, II on treadmill and 3-minute recovery afterwards.	Heart rates recorded simultaneously from rest (unclear position), treadmill exercise and 3-minute recovery (unclear position). Measurements comparing ECG to PPG performed during all phases (unclear if all time spent recorded, or 1-minute subsets).
Plews DJ, et al.	ECG 12-lead system (Cosmed). Smartphone (OS not specified) and Polar H7 data collected using in-house built application. ECG used standard 12-lead placement. Polar H7 fitted below fifth intercostal space. Fingertip used over smartphone camera sensor.	Alignment of ECG, Polar H7 and smartphone data output was manually performed after H7/smartphone data was collected from commercial program "HRV4Training.com"	Healthy subjects (N=29, 22 males; BMI 23.7 ± 2.3) beginning middle age (31 ± 10 years). 3 Elite athletes, 13 well-trained athletes, 10 recreationally trained athletes	Observational, with single study arm. Subjects performed guided (5 min) and normal breathing.	5-min recordings taken simultaneously (ECG, Polar H7 and smartphone with fingertip over camera) for normal and guided breathing.
Banhalmi A, et al.	PPG and ECG. PPG recorded using PPG recorded using iPhone 6 smartphone camera; ECG recorded using Cardiax PC-ECG. PPG recorded from fingertip; ECG recorded from 4 limbs in separate channels.	Sampling performed with 50 Hz notch filter, 150 Hz lowpass filter and 0.01 Hz highpass filter. Pre-processing included lowpass filter of 80 Hz and highpass filter of 1 Hz utilized on both PPG and ECG.	Healthy subjects (N=50, males=39). Additional parameters not specified.	Observational, with single study arm. Subjects sat and performed ECG and PPG measurements for 5 minutes with no regulation in breathing	5 minute recordings in parallel in seated position (ECG and PPG from iPhone 6). Time domain measurements: SDNN, rMSSD, lnrMSSD, pNN50. Frequency domain measurements total power, LF (0.04-0.15 Hz), HF (0.15-0.4 Hz), LF/HF, and LF + HF

were healthy young adults including elite athletes, however this study was observational and only evaluated guided breathing rates and did not include any PRV measurements [37]. For a second paper, the subjects tested were healthy young adults including elite athletes, all of which used a commercial application "HRV4Training" [36,38-41]. However this study was observational and only evaluated a particular parameter - lnRMSSD - over short time intervals of 1 minute [37]. In a third paper, healthy subjects had time- and frequency-domain PRV measurements recorded in a 5-minute epoch while seated; no exercises were performed in this observational study [42]. Finally, for the fourth paper, the study population consisted of clinical patients with Cardiovascular Disease (CVD) [35]. Patients were tested according to two treadmill protocols (Bruce protocol I and II) as well as at rest before exercise and during a 3-minute recovery. Unfortunately, this paper did not provide an in-depth analysis of PRV through time-domain, frequency-domain or non-stationary analytics.

As smartphones utilizing PPG technology require software, likely multiple layers of software, to enable interpretation of the sensor(s) signal, we additionally performed a pilot search of currently available smartphone applications claiming the ability to input and interpret Heart Rate Variability (HRV although we use PRV as a more apt acronym) for Android or iOS devices through either the Play Store (Android) or Apple Store (Apple). The results of this search are presented in Table 4 (Android) and Table 5 (iOS), where we include applications with 500+ downloads only. Our search of smartphone applications resulted in at least 21 applications for Android OS and 21, mostly overlapping, applications for iOS, available as of September 2019. Some of these applications required payment to access HRV (PRV) data and interpretation and/or recommendations, and many applications claimed to not need a sensor, or implied equivalency to ECG or clinical measurements of HRV.

Discussion

Papers evaluating arm-wearable PPG-based devices generally used healthy and pre-middle aged to middle-aged subjects. Two papers described their included subject pool as having previously performed some type of exercising in general [43,44] although they did not mention using athletes or subjects using some type of training regimen, and one paper had no restriction on exercise [12]. The types of activities used for experimental purposes in these papers included treadmill-based activities [23,44,45], elliptical exercise, stair climbing, stationary cycling, and light weight-lifting [43] as well as - notably - activities of daily living [46] and outdoor running [47]. All the studies were observational in nature, and unfortunately, none evaluated PRV.

In five of the papers, the PPG signal was recorded from a device attached to a fingertip and connected to an iOS-using smartphone with a commercial software program to analyze data (iThlete). In these studies, subjects were young and healthy and were tested in states including pre-season and seasonal exercise - in four studies [38-41] - and cycle exercise with choice-reaction time (considered to require a form of sustained attention) tasks in two parallel study arms [48]. PRV was measured using a single time domain

Table 3. Papers containing experiments using Photoplethysmography (PPG) from a commercially available arm/finger-wearable device.

Study	PPG Technology (Hardware)	Data Processing	Subjects	Experimental Design	Analytic Measurements
Heathers JAJ	ECG recorded with Powerlab 8/30 in Lead II position. PPG recorded using IR LED (iThlete) attached to fingertip and iOS compliant smartphone.	PPG recording software is custom (iThlete). Software digitizes at 16-bit, lowpass filter at 5 Hz and resamples at 500 Hz.	Healthy subjects (N=10, males=6), young adults (21.5 ± 3.5 years old) in study arm 1. Healthy subjects (N=10, males=7), young adults (23.3 ± 2.9 years old) in study arm 2.	Observational with two study arms. Study arm 1 looked solely at comparing pulse (PRV) to sinus rhythm (HRV). Study arm 2, evaluated exercise and attention-based tasks.	Subjects were seated at rest for 10 minutes with final 5 minutes recording of ECG and PPG simultaneously. Subjects began at rest, performed an attention task, and then exercise (cycling at desk) with 5 minutes rest between.
El-Amrawy F and Nounou MI	Apple iWatch, Samsung Gear Fit, Samsung Gear 1, Samsung Gear 2, Samsung Gear S, iHealth Tracker (AM3), Pebble Steel, Pebble Watch, Qualcomm Toq, Motorola Moto 360, Garmin Vivofit, Mi Band, MisFit Shine, Jawbone Up, Nike+ Fuelband SE, Sony Smartwatch (SWR10), and FitBit Flex. Each participant wore 3 wearables on each arm. Each participant had corresponding smartphone to record data in back pockets. An Onyx Vantage 9590 professional clinical pulse oximeter recorded heart rate simultaneously.	Data were collected after each trial and statistics calculated on a trial-by-trial basis. Experimenters used wearable-provided heart rate measurements and step counts.	Healthy subjects (N=4) between 22-36 years of age.	Observational, single study arm. Subjects performed walking of various step counts to compare PPG wearables to Onyx Vantage 9590.	Subjects walked 3 different distances (200 m, 500 m, and 100 m) 40 separate times. Mean values for HR and step count were calculated. No description of whether each subject used each wearable, or what combinations occurred with the 17 wearables, was provided.
Parak J and Korhonen I	Mio Alpha, Schosche Rhythm wearable PPG devices. ECG employed 2 leads. Mio Alpha worn on wrist; Schosche Rhythm worn on anterior/lateral forearm just distal to elbow crease. ECG was placed according to two-channel Holter measurement.	Mio Alpha information transmitted to Garmin Forerunner for acquisition. Schosche Rhythm transmitted to iCardio Smartphone application. Embla Titanium wearable recorder was used to record ECG signal.	Healthy subjects (N=21, males=15) of beginning middle age (21.3 ± 10.7 years), that perform weekly "some kind of physical activity"	Observational, single study arm. Subjects performed resting, lying on a bed, standing, walking (3-5 km/h at 0-10% incline) running (9-11 km/h at 0% incline), resting, cycling (60-90 rpm) followed by more resting.	ECG signal was analyzed by Kubios HRV tool, that had an automatic R-peak detection algorithm. PPG and ECG signals were synchronized by applying a cross-correlation function and maximizing value at t=0.
Flatt, et al.	iThlete fingertip IR sensor and Polar T-31 chest strap	PPG recording software is custom (iThlete).	Healthy, young subjects (n=12, all female) from Div. 1 NCAA college soccer	Observational with single study arm. Subjects evaluated over 3 weeks (out of 3) of pre-season training camp.	Seated, 1 min recordings pre-training in the morning after arising from bed and evacuating bowels. Week 1 not used (training to use iThlete period). Breathing was spontaneous
Stahl SE, et al.	Scosche Rhythm, Mio Alpha, Fitbit Charge HR, Basis Peak, Microsoft Band, and TomTom Runner Cardio. Polar RS400 chest strap ECG also used. Each participant wore wearables according to manufacture criteria. All but Scoshe Rhythm were worn on the wrist (Scosche worn on inner/lateral forearm just distal to elbow crease). Polar RS400 was worn on the chest. Each participant wore 6 PPG monitors at once, 3 on each arm.	Data were collected after each trial and statistics calculated on a trial-by-trial basis. Subjects verbally told experimenters values to wearables in prescribed order. Experimenters used wearable-provided heart rate measurements and step counts.	Healthy subjects (N=50, males=32) between the ages of 19-45. Blood pressure <140/80 mm Hg.	Observational, single study arm. Participants walked and ran on the treadmill at 3.2, 4.8, 6.4, 8.0, and 9.6 km/h for 5 min at each protocol speed. Subjects then cooled down at 4.8 km/h for 5 min. On completion of the treadmill protocol, each subject had seated resting HR recorded every minute for 3 min.	HR measurements were recorded manually (verbally) every minute during 5, 5-minute treadmill walking/running speeds. 5 minutes of rest followed with HR recorded for each minute. 3 HR measurements on the minute for a 3-minute seated, resting recovery were recorded at the end of the treadmill running and rest.
Dooley EE, et al.	Apple Watch, Fitbit Charge HR, Garmin Forerunner 225. ECG used for comparison: Polar T31. Parvo Medics TrueOne 2400 (using Hans Rudolph pneumotachometer) used to measure ventilation. Randomized wrist location for all 3 wearables.	PPG devices had initial pre-processing performed by the device (as an end consumer would) and researchers recorded stated HR values, and EE measurements from the associated device applications.	Healthy students (N=62, males=36), of varying ethnicity (47% non-white), aged 18-38 years with BMI ranging from 17.1-45.0 kg/m^2	Observational, single-study arm. Subjects began seated (10 min) followed by 4, 4 min stages of treadmill exercise followed by 10 min seated recovery.	HR was measured 3.5 min into each 4 min stage, collected in random order (by device) and averaged together for HR during that stage.
Flatt, et al.	iThlete fingertip IR sensor	PPG recording software is custom (iThlete).	Healthy, young subjects (n=8, all female) from Div. 1 NCAA college soccer	Observational with single study arm. Subjects evaluated over 2 weeks (out of 3) of pre-season training camp.	Seated, 1 min recordings pre-training in the morning after arising from bed and evacuating bowels. Week 1 not used (training to use iThlete period). Breathing was spontaneous

Gorny AH, et al.	Fitbit Charge HR. For ECG and comparison, a Polar H6 (chest) monitor was used. FitBit HR was worn on the non-dominant wrist. Polar H6 was worn on the chest. An Actigraph GT3X+ logger was worn on the same arm as the FitBit.	Actigraph GT3X+ logged Polar H6 data sampling at 10 s intervals. FitBit data were downloaded from web server through a provided API. Time intervals for FitBit were irregular.	Healthy subjects (N=10, males=7), of average to slightly above average body fat composition (BMI 22.9 kg/m^2 ± 3.8)	Observational, single study arm. Subjects went through activities of daily living wearing both the PPG and ECG devices.	Subjects had 10 s ECG readings and 60 s PPG readings taken over the course of at least 8 valid days. Valid days appears to be constructed to mean at least 10 h of daily living activities.
Bellenger C, et al.	WHOOP 3.0 worn overnight.	WHOOP 3.0 data exported to custom Microsoft Excel sheet for data analysis.	Healthy elite, water polo athlete subjects (N=11, 20-40 years old).	Observational, longitudinal daily measurements over 16 weeks of pre-Olympic training.	Subjects were sleeping during recordings. HR and PRV (lnRMSSD) reported as CV of intra-individual variation during 7 day week.
Parak J, et al.	PulseOn PPG wearable (wrist) and a Samsung Galaxy S3 phone. ECG was performed by Polar V800 HR Monitor was used to monitor distance but not HR. In lab, PulseOn was used as well as RS800CX chest strap and respiratory gas analyzer face mask (Metalyzer 3B). PulseOn worn on wrist, Polar devices on chest.	PulseOn data was analyzed off-line after data collection during submaximal or maximal tests.	Healthy subjects (N=24, males=13), with ages ranging from 18-55 years. BMI ranged 18-30 kg/m^2.	Observational, single study arm. Subjects performed a submaximal outdoor running test (at least 20 min) and a maximal voluntary exercise test in laboratory. Order of maximal and submaximal tests was randomized.	HR data were re-sampled at 1.5 s intervals and synchronized by maximizing cross-correlation between signals at t=0. HR data were averaged over 5 s non-overlapping windows.
Flatt, et al.	iThlete fingertip IR sensor	PPG recording software is custom (iThlete).	Healthy, young subjects (n=25, all male) from Div. 1 NCAA college football (Univ. Alabama)	Observational with single study arm; prospective observational cohort. Subjects were grouped according to sport position. Subjects tested for return of HRV (PRV) to baseline levels between training days; Subjects also had chronic training load vs. chronic HRV (PRV) compared	Seated, 1 min recordings pre-training (60-90 min). Breathing was spontaneous
Sarhaddi F, et al.	ECG and PPG recorded using Shimmer3 ECG and Samsung Sport Gear smartwatch	PPG data extracted using a feature-detection algorithm and ECG data extracted through proprietary software	28 subjects (14 male, 14 female) recorded during waking and sleep	Observational study over a single 24-hour window. Subjects did not record exercise time or method	5 minute windows during awake hours were analyzed for various time domain and FD PRV metrics.

Table 4. Commercially available smartphone applications for Android devices (as of Feb 2024).

Application	Stated Measurement Abilities	Cost
BLE Heart Rate & HRV	Bluetooth smart Heart Rate Monitor & Recorder with HRV Capability (in real time)	Free
Camera Heart Rate Variability	Camera HRV lets you check stress level without requiring any sensor	$4.49
EC-HRV test	Provides a test for rest and exercise measurements diagnosis	Free
Elite HRV	True Heart Rate Variability (HRV), Improve Health, Performance, Recovery, Stress	Free, In-app purchases
Heart Rate Variability HRV Camera (Early Access)	Measure Pulse, HRV, Fitness, Cardio, Stress	Free
HRV Breathing Rhythms	Present consecutive breathing rhythms	Free
HRV Explorer	A tool for assessing cardiac autonomic control	Free
HRV Lite by CardioMood	Check your stress. Track recovery.	Free
HRV measurement using only camera and finger!	HRV measurement using only camera and finger!	Free
HRV Stress Detector	Zero stress with guided deep breathing and HRV monitoring	Free
HRV4Training	HRV4Training helps optimize goals and improve performance. No sensors needed.	$9.99
iPulsus HRV Walking	Do as much sports as your heart allows with smart training plan	Free
Kardia - Deep Breathing Relaxation	Deep breathing exercise for stress relief, relaxation, meditation & better sleep	Free
METAFIT - HRV Personal Trainer	Custom-built workout program tailored to your unique goals	Free
Selfloops HRV	Measures and displays heart rate variability	Free
SweetBeat HRV	Clinical grade Heart Rate Variability for Training, Recovery & Stress	$4.99
Welltory - EKG Heart Rate Monitor, HRV Stress Test	Biofeedback, Pulse ECG, Heartbeat Cardiogram	Free

calculation, Root Mean Square of Standard Deviation (lnRMSSD), during the morning before any athletic activity and was not used as a decision metric for any training or exercise selection or modification.

This search of primary academic manuscripts using Photoplethysmography (PPG) technology employed on a wearable device for athletes, athletics, or training, identified a small number of papers (n=16). This outcome was surprising given the number of years since PPG was introduced as a technology able to record and calculate Pulse Rate (PR) and Pulse Rate Variability (PRV). Previous papers and reviews using ECG/EKG have shown sustained interest and experiments utilizing ECG/EKG technology for athletics, athletes and training that have developed ideas relating to training adaptation [26,49,50], recovery [51,52], detraining [53], exercise cycle programming [54], predicting athletic performance [55], or overtraining [5,56,57].

Table 5. Commercially available smart phone applications for iOS devices (as of Feb 2024).

Application	Stated Measurement Abilities	Cost
Camera Heart Rate Variability	Camera HRV lets you check stress level without requiring any sensor	$6.99
DailyBeat HRV	Our clinical grade algorithms measure Heart Rate Variability (HRV) and provide you with intuitive and easy to understand health status.	Free
EC-HRV test	Provides a test for rest and exercise measurements diagnosis	Free
Elite HRV	True Heart Rate Variability (HRV), Improve Health, Performance, Recovery, Stress	Free, In-app purchases
Healthzilla: HRV & Stress Scan	Types of data we analyze: Resting Heart Rate ("RHR"), Heart Rate Variability ("HRV")	Free
Heart Rate Variability (HRV) Bundle	Bundle includes 3 Heart Rate Variability (HRV) apps either using the camera, or Bluetooth low energy sensors (or both), to compute, record, store and export heart rate and heart rate variability data.	$14.99
HeartBreath	Live display of the current heart rate and variability values while recording.	$3.99
HeartRate+ Coherence PRO	Real Time Heart Rate Variability (HRV) Monitor	Free / $3.99
HEARTshape	HEARTshape measures your heart rate using your iPhone camera and flash.	Free
HRV Care	Heart Rate Variability (HRV) is a great indicator of what is going on inside your body.	Free
HRV4Training	HRV4Training helps optimize goals and improve performance. No sensors needed.	$9.99
Inner Balance	Inner Balance gets your heart, mind and emotions in sync to improve health, well-being and performance.	Free
Kardia - Deep Breathing Relaxation	Deep breathing exercise for stress relief, relaxation, meditation & better sleep	Free
O_2 Care - SpO_2 HRV Biofeedback	HRV Analysis. Resonance Breath (HRV Biofeedback).	Free
RhythmCor Ai	Continuous Heart Rate (HR) and HRV monitoring using novel augmented machine learning algorithms with contextual biometric based insights	Free
Selfloops HRV	Measures and displays heart rate variability	Free
Stress Guide: HRV & Meditation	Measure your pulse, HRV, stress levels and relax with guided meditations, relaxation.	Free
StressEraser Pro	StressEraser Pro is a handsome, simple and sensitive device to measure Heart Rate Variability (HRV) with your iPhone.	Free
SweetBeat HRV	Clinical grade Heart Rate Variability for Training, Recovery & Stress	$9.99
Wattson Blue	Optimize your training and recovery with HRV and other well-being metrics.	Free
Welltory - EKG Heart Rate Monitor, HRV Stress Test	Measures stress, energy, and productivity in 2 minutes every morning	Free

Table 6. Commercially available wearable devices claiming PPG-based HRV (PRV) data collection and analysis (as of Sep 2019).

Company	Product	Notes	Feature-Technology
Biovotion	Everion	HR, blood oxygenation, HRV, respiration rate, skin temperature, steps, sweat, sleep tracking, energy expenditure.	Accelerometer, PPG, Skin Temperature Sensor
Garmin	Fenix 5S plus	Gyroscope, compass, Step tracker, sleep tracking, accelerometer, water resistant (10 atm), Bluetooth, wi-fi, ant+, battery life 11 hours GPS, up to 7 days, thermometer, GPS, floors climbed, HRV, HR broadcast, vertical oscillation ratio, ground contact time, stride length, cadence	GPS, GLONASS, Galileo, Altimeter, Compass, Gyroscope, Thermometer, Accelerometer, Bluetooth, ANT+, Wi-Fi, Garmin Elevate
Garmin	Fenix 5	Step tracker, sleep tracking, accelerometer, water resistant (10 atm), altimeter, gyroscope, compass, Bluetooth, wi-fi, ant+, thermometer, GPS, floors climbed, HRV, HR broadcast, vertical oscillation ratio, ground contact time, stride length, cadence	Water Resistant (10 m), GPS, GLONASS, Garmin Elevate, Altimeter, Compass, Gyroscope, Accelerometer, Thermometer, Bluetooth, ANT+, Wi-Fi
Oura	Oura ring	HR, accelerometer, gyroscope, temperature, battery life 7 days, water resistant (100 m), Bluetooth, sleep tracking, HR, HRV claimed	Accelerometer, Gyroscope, LEDs (PPG?), Body Temperature
Salutron	Zoom HRV	HR, sleep monitoring, HRV	PPG, accelerometer
BioStrap	BioStrap	HR, HRV, respiratory rate, blood oxygen saturation, sleep analysis	PPG, Bluetooth, 3-axis accelerometer, gyroscope
Whoop	Strap	HR, HRV, sleep tracking	PPG, accelerometer (?)
iThlete	Finger Sensor	IR PPG sensor at fingertip	PPG

In addition, the rapid growth in sold wearable devices containing PPG, claiming the ability to sense, interpret, and analyze HRV (PRV), led us to anticipate that significantly more research had been presented:

a) Validating PPG as used by current, commercial devices

b) Validating comparisons of PRV from PPG signals from commercial devices to ECG signals, and

c) Employing PRV to better elucidate recommendations for athletic exercise.

The number of papers we uncovered was even lower when considering wearable devices available commercially rather than recording machines/ software custom built or meant for the lab environment [5,58,59]. A selection of these commercially available wearable devices claiming the ability to measure and analyze HRV (PRV), as of February 2024, is presented in Table 6.

Conclusion

In conclusion, this review did not identify a significant body of scientific literature using commercially available PPG devices to measure PRV and inform decisions for athletes, athletics, or exercise training. Academic, lab-based studies offer an important class of research to validate technology, analytics, and utilized statistics, explore treatment variable responses, probe causation of perturbations, and inform reasonable recommendations based on data. Without a clinical body of literature, there is concern over the usage and reliability of recommendations that are currently available to the general public through wearable devices or smartphone applications. The easy availability and breadth of devices and applications for use by athletes outside of the lab, raises particularly important questions as these products claim PPG is a valid and equivalent measurement tool as HRV which has a longstanding and robust medical literature built upon its particular technology and underlying physiology.

Caution is required in evaluating commercial PPG-based PRV and drawing inferences in comparison to ECG-based HRV treatment conclusions or recommendations, particularly outside of the lab environment. Field studies (sometimes termed RWRD) are a complementary class of studies to lab-based Randomized Control Trials (RCTs) that may help address real-world usage, clinical decisions, adherence/compliance, potential benefits, and risks. Our literature search identified only observational trials and no controlled trials. Very few field studies have been attempted using a smartphone and of those, the device was used to record 1 minute HRV (PRV). There is currently a lack of data evaluating PPG for PRV, what PRV means physiologically in relation to athletics and exercise training, or how to use it over time to affect positive performance adaptations.

Recommendations for Further Studies

Recommendations for further studies include three broad themes

a) Further lab-based clinical trials to evaluate commercially available wearable devices using PPG technology to record PRV. These trials shouldn't simply compare PRV to HRV, as there is reason to expect different responses based on different technology (ECG field electrical measurement *vs.* PPG diode light reflectance), different underlying physical processes (ECG-recorded electrical properties of the heart nerve cells *vs.* PPG-recorded light-reflecting compound density changes in distal blood vessels), and different effector physiological systems (ECG influenced by respiration/electrical properties/ endocrine system/thermoregulation/blood pressure/other(?) *vs.* PPG influenced by respiration[60]/blood pressure(?)/endocrine system(?)/ thermoregulation(?)/dehydration(?)/other(?)). These trials should be designed to take advantage of the best capabilities of lab-based clinical experimental design to probe what physiological processes affect PPG measurements from commercial devices.

b) Further Real-world Real Data Studies (RWRD, or field studies) to inform usage characteristics and capabilities for PPG-technology in commercially available wearable devices. These studies should incorporate not only observational analysis, but interventions and experiments designed to probe adherence/compliance, effectiveness, limitations and risks for an athlete in the real-world setting. In addition, the concept of exercise and training requires time for measurable effects. However, the vast majority of PPG technology studies to date appear to reflect on single episodes of contiguous time for data collection rather than repeated measures at frequent intervals to judge effectiveness of interventions and recommendations.

c) Usage and exploration of alternative, specialized measurements and analytic statistics to acknowledge the probable complimentary, rather than supplementary, nature of PRV to HRV and the intra-individual training needs for athletes as opposed to comparisons to a generalized sample population. Indeed, cases of extreme variation in measured HRV values [26] and diametrically opposed anticipated performance results after ECG-based HRV measurements [61] have already been noted with healthy, younger subjects and elite-level athletes.

Acknowledgement

Authors would like to extend gratitude to Aaron McGee PhD, David Mordecai PhD, and Samantha Kappagoda for critical reading of this manuscript. In addition, authors would like to thank Lawler Watkins for significant help in manuscript preparation.

Conflict of Interest

The author states no conflicts of interests. M. R. Coggins currently works for Replicate International Inc and Equinox Holdings Inc. Replicate International acts in advisory, technological review and educational roles related to technology, health and wellness, and athletics and performance. Neither Replicate International nor Equinox Holdings have current business relationship to any companies manufacturing or selling wearable technology. All work in preparation of this manuscript was completed under the auspices of Replicate International, solely completed by M. R. Coggins, and does not represent the views or work of Numerati Partners nor Equinox Holdings Inc.

References

1. Rowell, Loring B., Henry L. Taylor and Yang Wang. "Limitations to prediction of maximal oxygen intake." *J Appl Physiol* 19 (1964): 919-927.
2. Jetté, Maurice, John Campbell, Jean Mongeon and Richard Routhier. "The Canadian home fitness test as a predictor of aerobic capacity." *Can Med Assoc J* 114 (1976): 680.
3. Shephard, RJ. "Article Sports Medicine I." (1984).
4. Billman, George E. "Heart rate variability-a historical perspective." *Front Physiol* 2 (2011): 16984.
5. Aubert, André E., Bert Seps and Frank Beckers. "Heart rate variability in athletes." *Sports Med* 33 (2003): 889-919.
6. Mulder, G and W. R. E. H. Mulder-Hajonides van der Meulen. "Mental load and the measurement of heart rate variability." *Ergon* 16 (1973): 69-83.
7. Zwaga, Harm Jitse Gerard. "Psychophysiological reactions to mental tasks: Effort or stress?." *Ergon* 16 (1973): 61-67.
8. Camm, A. John, Marek Malik, J. Thomas Bigger and Günter Breithardt, et al. "Heart rate variability: Standards of measurement, physiological interpretation and clinical use. Task force of the European society of cardiology and the north American society of pacing and electrophysiology." *Circ* 93 (1996): 1043-1065.
9. Kleiger, Robert E., J. Philip Miller, J. Thomas Bigger Jr and Arthur J. Moss. "Decreased heart rate variability and its association with increased mortality after acute myocardial infarction." *Am J Card* 59 (1987): 256-262.
10. Chapleau, Mark W. and Rasna Sabharwal. "Methods of assessing vagus nerve activity and reflexes." *Heart Fail Rev* 16 (2011): 109-127.
11. Freeman, Roy and Mark W. Chapleau. "Testing the autonomic nervous system." *Handb Clin Neurol* 115 (2013): 115-136.
12. Dong, Jin-Guo. "The role of heart rate variability in sports physiology." *Exp Ther Med* 11 (2016): 1531-1536.
13. Abramson, DI, K. Jochim and E.A. Ctjller. Downloaded from www.physiology.org/ journal/ajplegacy at New York Univ (128.122.149.092) on [Internet].
14. Antink, Christoph Hoog, Steffen Leonhardt and Marian Walter. "Local interval estimation improves accuracy and robustness of heart rate variability derivation from photoplethysmography." In 2018 40th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), IEEE (2018): 3558-3561.
15. Allen, John. "Photoplethysmography and its application in clinical physiological measurement." *Physiol Meas* 28 (2007): R1.
16. Hayano, Junichiro, Allan Kardec Barros, Atsunori Kamiya and Nobuyuki Ohte, et al. "Assessment of pulse rate variability by the method of pulse frequency demodulation." *Biomed Eng Online* 4 (2005): 1-12.
17. Lu, Guohua, F. Yang, J. Andrew Taylor and John F. Stein. "A comparison of photoplethysmography and ECG recording to analyse heart rate variability in healthy subjects." *J Med Eng Technol* 33 (2009): 634-641.
18. Allen, John and Alan Murray. "Age-related changes in the characteristics of the photoplethysmographic pulse shape at various body sites." *Physiol Meas* 24 (2003): 297.
19. Shin, Hangsik. "Ambient temperature effect on pulse rate variability as an alternative to heart rate variability in young adult." *J Clin Monit Comput* 30 (2016): 939-948.
20. Gil, Eduardo, Michele Orini, Raquel Bailon and José María Vergara, et al. "Photoplethysmography pulse rate variability as a surrogate measurement of heart rate variability during non-stationary conditions." *Physiol Meas* 31 (2010): 1271.

21. Institute of Electrical and Electronics Engineers. Kerala Section, IEEE Region 10, Institute of Electrical and Electronics Engineers. IEEE TENSYMP 2017 : IEEE International Symposium on Technologies for Smart Cities: 14-16 July, 2017, Kochi, Kerala, India.

22. Reyners, A. K. L., B. P. C. Hazenberg, W. D. Reitsma and A. J. Smit. "Heart rate variability as a predictor of mortality in patients with AA and AL amyloidosis." *Eur Heart J* 23 (2002): 157-161.

23. El-Amrawy, Fatema and Mohamed Ismail Nounou. "Are currently available wearable devices for activity tracking and heart rate monitoring accurate, precise, and medically beneficial?." *Healthc Inform Res* 21 (2015): 315.

24. Schäfer, Axel and Jan Vagedes. "How accurate is pulse rate variability as an estimate of heart rate variability?: A review on studies comparing photoplethysmographic technology with an electrocardiogram." *Int J Cardiol* 166 (2013): 15-29.

25. Georgiou, Konstantinos, Andreas V. Larentzakis, Nehal N. Khamis and Ghadah I. Alsuhaibani, et al. "Can wearable devices accurately measure heart rate variability? A systematic review." *Folia Medica* 60 (2018): 7-20.

26. Plews, Daniel J., Paul B. Laursen, Jamie Stanley and Andrew E. Kilding, et al. "Training adaptation and heart rate variability in elite endurance athletes: Opening the door to effective monitoring." *Sports Med* 43 (2013): 773-781.

27. Shah, Mansoor Hussain, Syed Absar Kazmi, Khairul Azami Sidek and Sheroz Khan. "Power Spectrum Density based analysis of Photolythsmographic signal for different physiological conditions." In 2014 IEEE International Conference on Smart Instrumentation, Measurement and Applications (ICSIMA), IEEE (2014): 1-6.

28. IEEE Engineering in Medicine and Biology Society. Annual International Conference (38th : 2016 : Orlando Fla), IEEE Engineering in Medicine and Biology Society, Institute of Electrical and Electronics Engineers. 2016 38th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC): 16-20 Aug. 2016.

29. Lan, Kun-chan, Paweeya Raknim, Wei-Fong Kao and Jyh-How Huang. "Toward hypertension prediction based on PPG-derived HRV signals: A feasibility study." *J Med Syst* 42 (2018): 1-7.

30. Zhang, Zhilin, Zhouyue Pi and Benyuan Liu. "TROIKA: A general framework for heart rate monitoring using wrist-type photoplethysmographic signals during intensive physical exercise." *IEEE Trans Biomed Eng* 62 (2014): 522-531.

31. Chriskos, P., J. Munro, V. Mygdalis and I. Pitas. "Hindering. In 2017 IEEE Global Conference on Signal and Information Processing (GlobalSIP 2017): Proceedings of a meeting held 14-16 November 2017, Montreal, Quebec, Canada. Institute of Electrical and Electronics Engineers (IEEE)." (2017): 403-307

32. Selvaraj, Nandakumar, Ashok Jaryal, Jayashree Santhosh and Kishore K. Deepak, et al. "Assessment of heart rate variability derived from finger-tip photoplethysmography as compared to electrocardiography." *J Med Eng Technol* 32 (2008): 479-484.

33. IEEE Engineering in Medicine and Biology Society. Annual International Conference (36th : 2014 : Chicago Ill), IEEE Engineering in Medicine and Biology Society, Institute of Electrical and Electronics Engineers. Engineering in Medicine and Biology Society (EMBC), 2014 36th Annual International Conference of the IEEE : date 26-30 Aug. 2014.

34. IEEE Engineering in Medicine and Biology Society. Annual International Conference (37th : 2015 : Milan I, IEEE Engineering in Medicine and Biology Society, Institute of Electrical and Electronics Engineers. 2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC) : date 25-29 Aug. 2015.

35. Lee, Eun Sun, Jin Seok Lee, Min Cheol Joo and Ji Hee Kim, et al. "Accuracy of heart rate measurement using smartphones during treadmill exercise in male patients with ischemic heart disease." *Ann Rehabil Med* 41 (2017): 129.

36. Altini, Marco and Oliver Amft. "HRV4Training: Large-scale longitudinal training load analysis in unconstrained free-living settings using a smartphone application." In 2016 38th *Annu Int Conf IEEE Eng Med Biol Soc* (EMBC), IEEE (2016): 2610-2613.

37. Plews, Daniel J., Ben Scott, Marco Altini and Matt Wood, et al. "Comparison of heart-rate-variability recording with smartphone photoplethysmography, polar H7 chest strap, and electrocardiography." *Int J Sports Physiol Perform* 12 (2017): 1324-1328.

38. Flatt, Andrew A. and Michael R. Esco. "Evaluating individual training adaptation with smartphone-derived heart rate variability in a collegiate female soccer team." *J Strength Cond Res* 30 (2016): 378-385.

39. Flatt, Andrew A., Michael R. Esco and Fábio Y. Nakamura. "Individual heart rate variability responses to preseason training in high level female soccer players." *J Strength Cond Res* 31 (2017): 531-538.

40. Flatt, Andrew A., Michael R. Esco, Jeff R. Allen and James B. Robinson, et al. "Heart rate variability and training load among national collegiate athletic association division 1 college football players throughout spring camp." *J Strength Cond Res* 32 (2018): 3127-3134.

41. Flatt, Andrew A., Bjoern Hornikel and Michael R. Esco. "Heart rate variability and psychometric responses to overload and tapering in collegiate sprint-swimmers." *J Sci Med Sport* 20 (2017): 606-610.

42. Bánhalmi, András, János Borbás, Márta Fidrich and Vilmos Bilicki, et al. "Analysis of a pulse rate variability measurement using a smartphone camera." *J Healthc Eng* 2018 (2018).

43. Spierer, David K., Zohn Rosen, Leib L. Litman and Kenji Fujii. "Validation of photoplethysmography as a method to detect heart rate during rest and exercise." *J Med Eng Technol* 39 (2015): 264-271.

44. Stahl, Sarah E., Hyun-Sung An, Danae M. Dinkel and John M. Noble, et al. "How accurate are the wrist-based heart rate monitors during walking and running activities? Are they accurate enough?." *BMJ Open Sport Exerc Med* 2 (2016): e000106.

45. Dooley, Erin E., Natalie M. Golaszewski and John B. Bartholomew. "Estimating accuracy at exercise intensities: A comparative study of self-monitoring heart rate and physical activity wearable devices." *JMIR Mhealth Uhealth* 5 (2017): e7043.

46. Gorny, Alexander Wilhelm, Seaw Jia Liew, Chuen Seng Tan and Falk Müller-Riemenschneider. "Fitbit charge HR wireless heart rate monitor: Validation study conducted under free-living conditions." *JMIR Mhealth Uhealth* 5 (2017): e8233.

47. Parak, Jakub, Maria Uuskoski, Jan Machek and Ilkka Korhonen. "Estimating heart rate, energy expenditure, and physical performance with a wrist photoplethysmographic device during running." *JMIR Mhealth Uhealth* 5 (2017): e7437.

48. Heathers, James AJ. "Smartphone-enabled pulse rate variability: An alternative methodology for the collection of heart rate variability in psychophysiological research." *Int J Psychophysiol* 89 (2013): 297-304.

49. Heffernan, Kevin S., Christopher A. Fahs, Kevin K. Shinsako and Sae Young Jae, et al. "Heart rate recovery and heart rate complexity following resistance exercise training and detraining in young men." *Am J Physiol Heart Circ Physiol* 293 (2007): H3180-H3186.

50. Prinsloo, Gabriell E., HG Laurie Rauch and Wayne E. Derman. "A brief review and clinical application of heart rate variability biofeedback in sports, exercise, and rehabilitation medicine." *Phys Sportsmed* 42 (2014): 88-99.

51. Chen, Jui-Lien, Ding-Peng Yeh, Jo-Ping Lee and Chung-Yu Chen, et al. "Parasympathetic nervous activity mirrors recovery status in weightlifting performance after training." *J Strength Cond Res* 25 (2011): 1546-1552.

52. Edmonds, R. C., W. H. Sinclair and A. S. Leicht. "Effect of a training week on heart rate variability in elite youth rugby league players." *Int J Sports Med* (2013): 1087-1092.

53. Gamelin, Francois-Xavier, Serge Berthoin, H. Sayah and C. Libersa, et al. "Effect of training and detraining on heart rate variability in healthy young men." *Int J Sports Med* (2007): 564-570.

54. Kiviniemi, Antti M., Arto J. Hautala, Hannu Kinnunen and Mikko P. Tulppo. "Endurance training guided individually by daily heart rate variability measurements." *Eur J Appl Physiol* 101 (2007): 743-751.

55. Buchheit, M., M. B. Simpson, H. Al Haddad and P. C. Bourdon, et al. "Monitoring changes in physical performance with heart rate measures in young soccer players." *Eur J Appl Physiol* 112 (2012): 711-723.

56. Hynynen, E. S. A., Arja Uusitalo, Niilo Konttinen and Heikki Rusko. "Heart rate variability during night sleep and after awakening in overtrained athletes." *Med Sci Sports Exerc* 38 (2006): 313-317.

57. Baumert, Mathias, Lars Brechtel, Jürgen Lock and Mario Hermsdorf, et al. "Heart rate variability, blood pressure variability, and baroreflex sensitivity in overtrained athletes." *Clin J Sport Med*16 (2006): 412-417.

58. Bellenger, Clint R., Dean Miller, Shona L. Halson and Gregory D. Roach, et al. "Evaluating the typical day-to-day variability of WHOOP-derived heart rate variability in olympic water polo athletes." *Sensors* 22 (2022): 6723.

59. Chen, Xiang, Yuan-Yuan Huang, Feng Yun and Tian-Jun Chen, et al. "Effect of changes in sympathovagal balance on the accuracy of heart rate variability obtained from photoplethysmography." *Exp Ther Med* 10 (2015): 2311-2318.

60. Plews, Daniel J., Paul B. Laursen, Andrew E. Kilding and Martin Buchheit. "Heart rate variability in elite triathletes, is variation in variability the key to effective training? A case comparison." *Eur J Appl Physiol* 112 (2012): 3729-3741.

61. Yuda, Emi, Muneichi Shibata, Yuki Ogata and Norihiro Ueda, et al. "Pulse rate variability: A new biomarker, not a surrogate for heart rate variability." *J Phys Anthropol* 39 (2020): 1-4.

How to cite this article: Coggins R. Michael. "Exercise and Real-world Training Using Pulse Rate Variability: A Systematic Review of Wearable Photoplethysmography Technology and Real-world Interventions." *Int J Health Med Informat* 15 (2024): 516.