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Article

The based-biofeedback approach versus ECG for evaluation heart rate variability during the maximal exercise protocol among healthy individuals

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Abstract: Although the use of biofeedback devices is beyond measure, they are widely applied only for clinical purposes. Therefore, this study evaluated whether biofeedback devices could be applied to estimate heart rate variability (HRV) among healthy populations. 60 individuals (46 ± 5 years; 30 women) performed maximal exercise protocol (MEP). At pre- and post-MEP status, HRV indexes were collected by two devices: 1) the electrocardiogram device (ECG); 2) the biofeedback device (BIO). At pre-exercise status, all HRV parameters had significant correlations, ranging from low (r = 0.241) to high (r = 0.779). At post-exercise status, significant correlations for some of the HRV measures were found as well, ranging from low (i.e., $r \leq 0.29$) to moderate (i.e., $0.3 \leq r \leq 0.49$). According to our knowledge, this study is the first attempt to evaluate HRV by biofeedback devices among healthy individuals, which shows they can also be applied as a swift method to examine HRV among healthy individuals, especially in rest conditions.

Keywords: heart rate variability; electrocardiogram; biofeedback; physical activity; healthy population

1. Introduction

As a response to any sudden physical challenges, the cardiovascular system can be modified to maintain homeostasis, which means heartbeats constantly change [1]. The heart rate variability (HRV), quantified by the fluctuations in R-wave to R-wave intervals (RRI), has constituted a useful non-invasive method to evaluate autonomic activity, particularly parasympathetic tone and sympathy-vagal balance at either rest or any physical activities [2–5]. As the cardiovascular system responds to stressors, HRV may predict certain diseases [6–8]. Plus, it can be useful to monitor high performance during training sessions [9–11]. Meanwhile, the literature on autonomic activation has explained that the reduction in HRV, consisting of both higher sympathetic and lower parasympathetic activities, can be considered a frequent marker of abnormal and insufficient autonomic nervous system (ANS) adaptation [2,12,13] and the elevation in blood pressure variability [14], which possibly indicates a low heart capacity to respond to multiple physiological and environmental stimuli [14–17], which is associated with diverse pathological conditions such as coronary heart disease and mortality [18–20], future functional decline [21], chronic heart failure [22], sarcopenia [23], and hypertension [24]. Whereas, high HRV, known as an indicator of evaluated parasympathetic and reduced sympathetic activities, illustrates a good body adaptation [25,26]. Recently, it has been reported that physical exercise, both aerobic and resistance training, influences the cardiovascular system positively, especially

vagal activity as its important determinant [27–30], which can be considered the cornerstone of nonpharmacological treatment and prevention of such diseases [31–35]. To illustrate, various exercise methods, practically aerobic, alter the cardiac-autonomic balance, including increasing vagal autonomic drive while lessening sympathetic drive [31–39]. Indeed, the studies have been conducted among healthy children [40], young adults [41], and patients [42–44] following performing the aerobic [44,45], resistance [46], or interval training interventions [47] protocols.

Besides, sports and training sciences also pay attention to either time- or frequency-domain HRV indices, which means HRV is applied as the noninvasive method to measure autonomic changes following short- and long-term endurance training among individuals performing leisure sports activities and high-performance training [48]. These changes are followed up by a notable reduction of heart rate at either rest status or during submaximal exercise conditions, reflecting the elevation activity of the autonomic efferent and shifting in favor of vagal-activity enhancement to modulate the cardiac rhythm [48]. In other words, HRV kinetics may predict aerobic fitness and exercise performance during sub- or maximal workouts [49–51], which is also known as a key marker to evaluate fatigue intensity [52] and a diagnostic marker of overreaching and overtraining [48]. Generally, the whole study literature declares the vital necessity of assessing HRV among various populations to monitor their health status and performance regardless of both the type and intensity of exercise.

Recently, although trended smartwatches (i.e., Apple Watch, Garmin, Fitbit, Polar, and Samsung Galaxy Watch) are being evaluated for HRV estimating accuracy related to stress management features [53–55], generally, devices such as clinical multi-lead ECG systems (e.g., Holter ECGs) [56], photoplethysmography (PPG) [57,58], the Faros^{TM} ECG [59–61], the Actiheart [62], the AidlabTM [63,64], and Polar H [57,65] have been applied to assessing HRV indices regarding the large series of evidenceDespite this, over a seven-decade period, electrocardiograms (ECG) have become the most routine to monitor HRV [12,66,67]. ECG can be interchanged by either the Polar (i.e., S810i and V800) or Suunto t6 instruments to record the R-R intervals in both healthy (i.e., runners) and patient populations [68–70]. The 12-lead ECG, which is also known as the golden standard, consists of three bipolar-limb- leads (i.e., I, II, and III), three unipolar-augmented- leads (i.e., aVL, aVR, and aVF), and six unipolar chest leads, including V1–V6 [67,71]. Nevertheless, some items are crucial to measuring HRV indices by this device, such as the correct placement of each lead reported by various studies [67,71,72] and it also requires both expertise and time.

On the other hand, HRV-biofeedback (HRV-bio) devices impact clinical therapeutics in various diseases [73]. Regarding some evidence, HRV-bio is known as an effective non-pharmacological intervention to monitor autonomic balance [12,74] which has skin conductance that can be applied as direct quantitative ANS markers [75], expressing its potential value in chronic disease management [76]. In general, HRV-bio has been applied as a training method to enhance sports and workout performance [77–79]. For instance, the HRV-bio has been considered a technique for managing stress based on longer exhalations and slower respiration training [80,81], and based on our knowledge, only a few papers have used biofeedback devices as an HRV measurement method [79]. Thus, applying HRV-bio would be considered another option for measuring HRV among healthy populations.

Taken together, HRV could be estimated by calculating the R-R intervals through various devices. Although the 12-lead ECG is the standard method to measure the HRV, it requires special items (i.e., expertise and time). On the other hand, it has been expressed that HRV measurements generated by a 12-lead ECG, a Holter-style ambulatory recording system, and a custom-built chest strap (strap) would not agree well in all cases [45]. Despite this, to the best of our knowledge, applying HRV-bio has been overlooked as a real-time and swift-measurable method to measure HRV among healthy individuals, which can be considered crucial and required for monitoring HRV in healthy populations regardless of both the type and intensity of exercise. Therefore, we sought to assess the accuracy between ECG (as the golden method) and BIO, which means approaching HRV by biofeedback device would be authentic at rest status (pre-exercise condition), and whether this situation would remain the same after performing a maximal exercise protocol (MEP) (at post-exercise status) among healthy individuals.

2. Materials and methods

2.1. Ethical approval

In this investigation, the local institutional ethics committee reviewed and approved all the methods and data collection (Ethical Code: IR.UMZ.REC.1397.019). It should be mentioned that the whole research process was performed according to the 1964 Helsinki Declaration [82]. In this regard, all healthy males and females had the opportunity to participate and obtain informed consent. In addition, the testing procedures, protocols, and equipment were introduced to participants, making them familiar with the research process. Meanwhile, the opportunity was provided for each individual to query any progress section whenever it was not comprehensible. Essentially, leaving and/or withdrawing the study progress without any consequences was the individuals' right when they did not want to keep on participating.

2.2. Study design

In this study, the HRV simultaneously was recorded during pre- and post-exercise status to estimate the correlation between the HRV indices extracted by two measurement devices, i.e., the electrocardiogram (ECG) and the biofeedback (BIO).

2.3. Participants, inclusion, and exclusion criteria

In this study, 60 healthy, qualified-volunteered individuals (30 females) participated. Additionally, we kindly asked participants to avoid strenuous exercise and to abstain from any food and beverages containing alcohol and caffeine 48 h before data collection. All procedures and measurements were conducted from 8:00 to 13:00.

In addition, to be eligible to remain in the investigation process, some existing requirements were seated, such as: 1) Not having a smoking habit and/or being exposed to second-hand smoke, 2) No consumption of any antioxidant supplements at least one month before the study, 3) No history of chronic cardiovascular events or pulmonary and inflammatory diseases; 4) Not having any other medical limitations,

including any physical disabilities and/or limitations of mobility. All study females were screened for the inclusion eligibility criteria. The survey included questions about the history of the menstrual period (present, irregular, or absent).

2.4. Anthropometric measurements

Before the exercise protocol, a specialized expert assessed participants' anthropometric characteristics [83]. In this case, a stadiometer was used to measure each individual's weight and height according to its height (about 0.1 cm) and weight (about 0.1 kg) accuracy. Moreover, a body composition analyzer device (Medigate Inc., BoCA x1, Korea) was applied to measure the body mass index (BMI). **Table 1** illustrates the participants' demographic characteristics.

Table 1. Demographics (mean ± standard deviation) of participants who completed.

Participant	Age (years)	Height (m)	Weight (kg)	BMI (kg/m^2)	Vo2max (mL kg^{-1} min^{-1})
Male (n = 30)	46.6 ± 4.9	1.70 ±0.07	85.35 ± 11.91	29.2 ± 3.1	34.55 ± 3.02
Female (n = 30)	44.37 ± 4.1	1.57 ± 0.05	72.15 ± 8.9	29.1 ± 3.04	32.94 ± 3.04

BMI—body mass index.

2.5. The maximal exercise protocol (MEP)

In this study, the Bruce protocol was applied as the maximal exercise protocol (MEP), consisting of a 3-minute stage workout that gradual elevation occurs in both speed and grade, subsequently, until the individual feels exhausted [84]. The exact details have been described previously [85]. Also, we encouraged the participants to continue the MEP until their maximal tolerance, which was the heart rate (HR) value, reached 80% to 90% of HRmax.

To assess the VO2max, the standard equation was the reference, which has been published elsewhere [86]. In this case, a calibrated treadmill (h/p/cosmos Sports and Medical GmbH, Mercury model, Nussdorf-Traunstein Germany) was applied while we evaluated the Borg 6–20 scale during the MEP, also known as the ratings of perceived exertion (RPE).

2.6. Kubios and biofeedback HRV analyses

Based on Kubios HRV analysis, HR and RR intervals were continuously recorded via standard 12-lead electrocardiography (Custo cardio 100, Custo med GmbH, Ottobrunn, Germany) at pre- (rest status including a 3-minute duration of HR stabilization) and post-exercise (instantly after performing MEP) conditions, with sampling rate set at 1000 Hz (at seated posture). Next, the investigators collected the RR intervals while visually inspecting and omitting any premature beats and artifact/noise from all recorded RR intervals. Then, we export all collected RR intervals from the ECG manufacturer's software (Medset, Hamburg, Germany) to analyze them by customized software (Kubios HRV software, version 2.1, Department of Applied Physics, University of Eastern Finland, Kuopio, Finland). Based on former evidence, there are no differences across various Kubios filter levels in adults [87]. Therefore, we used a very strong filter level in this study [88].

On the other hand, to assess HRV_{BIO}, data was recorded by a Biofeedback device

(version 4.2, Biofeedback 2000 x-pert software, made in Austria) from the pronation surface of the hand at pre- (rest status including a 3-minute duration of HR stabilization) and post-exercise (instantly after performing MEP) conditions, and the sampling rate was set at 1000 Hz as described previously [79,89]. Briefly, the blue electrode cable was attached to the back of the right hand, while the red one was attached in the same spot but to the left hand. Also, the black electrode cable was attached to the back of the non-dominant hand (i.e., the left hand for right-handed people) [90]. To prevent the noise, we tried to keep the reference constant.

In this study, measured indices of HRV consisted of time-domain variables (i.e., standard deviation of normal RR intervals, SDNN; root mean square of successive differences, RMSSD; the proportion of differences between adjacent NN intervals of more than 50 ms pNN50), frequency domain variables (i.e., the low-frequency band, LF (0.04–0.15 Hz), the high-frequency band, HF (0.15–0.40 Hz), the LF/HF ratio), and nonlinear measures (i.e., standard deviation of the instantaneous beat-to-beat RR interval variability or minor axis of the Poincare plot, SD1; the standard deviation of continuous long-term RR interval variability or major axis of the Poincare plot, SD2) [91,92].

2.7. Statistical analysis

The SPSS software (version 27.0 for Windows, IBM, Armonk, NY, USA) was applied for all statical analyses while we drew the figures with the GraphPad Prism® software (version 9 for Windows, GraphPad Software, Inc., La Jolla, CA, USA). Firstly, the normality distribution of data was analyzed using the Kolmogorov-Smirnov test. The Pearson correlation test was used to analyze the overall association between indices. Pearson correlation coefficient (r) from 0.3 to 0.5 was considered as low, 0.5 to 0.7 as moderate, and 0.7 to 0.9 as high correlation [93]. Intra-class correlation coefficient (ICC) analysis was also performed to examine the agreement between examined variables. Values for ICC were calculated using a 2-way mixed model and interpreted as excellent (0.90 or higher), good (0.75 to 0.90), moderate (0.50 to 0.75), or poor (below 0.50) [94]. Bland Altman analysis was also used to test the agreement between values of examined variables as well as to visually depict the individual dispersion patterns [95]. Data are reported by their mean standard deviation. In this study, $P < 0.05$ was settled as the significant value.

3. Results

3.1. Correlation and agreement between HRV indices at the pre-exercise status

At rest status, the HRV parameters were measured using the BIO and ECG devices and are presented in **Figure 1** and **Table 2**. Regarding the Pearson test, all HRV parameters had significant correlations ranging from low ($r = 0.241$) to high ($r = 0.779$), such as RR interval ($r = 0.639$, $p < 0.001$), SDNN ($r = 0.779$, $p < 0.001$), RMSSD ($r = 0.625$, $p < 0.001$), PNN50 ($r = 0.455$, $p < 0.05$), LF ($r = 0.524$, $p < 0.001$), HF ($r = 0.589$, $p < 0.001$), LF/HF ratio ($r = 0.559$, $p < 0.001$), and SD2 ($r = 0.313$, $p < 0.05$); except for SD1, which only showed a certain trend toward significance ($r =$

0.241, p = 0.064) (**Figure 1**). Similarly, based on intra-class correlation coefficient (ICC) analysis, the indices obtained from these measurement devices, including RR intervals (ICC = 0.780, $p < 0.001$), SDNN (ICC = 0.874, $p < 0.001$), RMSSD (ICC = 0.769, $p < 0.001$), and HF (ICC = 0.722, $p < 0.001$), showed a significant agreement (**Table 2**). Meanwhile, PNN50 (ICC = 0.612, p = 0.008), LF (ICC = 0.641, $p < 0.001$), and LF/HF ratio (ICC = 0.593, $p < 0.001$) illustrate a considerable relationship between BIO and ECG, while SD1 (ICC = 0.379, p = 0.035) and SD2 (ICC = 0.47, p = 0.008) had a slight correlation (**Table 2**).

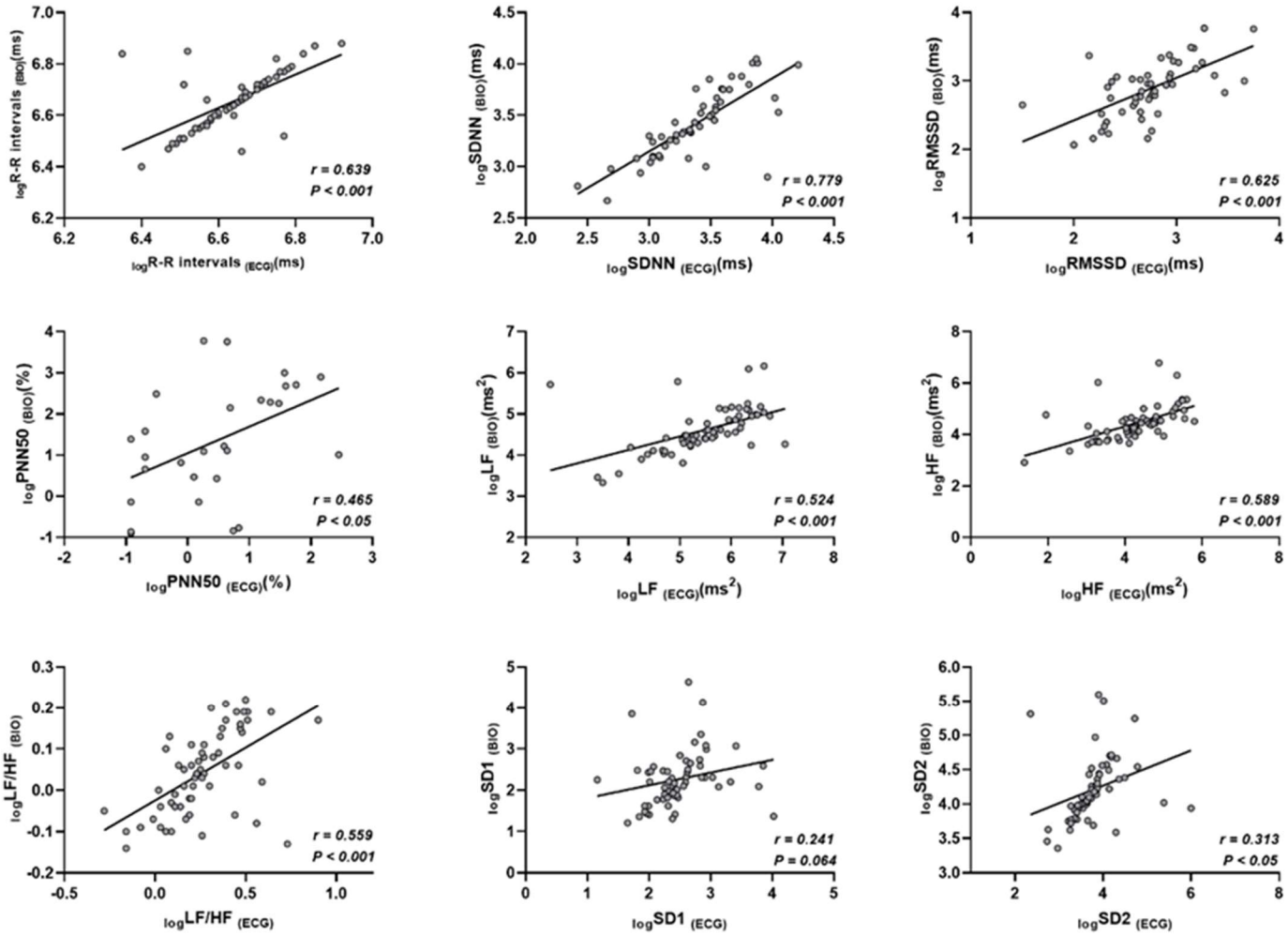

Figure 1. Pearson correlations between heart rate variability (HRV) parameters extracted via Kubios HRV and biofeedback device at pre-exercise status. Abbreviations: BIO, the biofeedback device; ECG, the electrocardiogram device; SDNN, Standard deviation of NN intervals; RMSSD, Root mean square of successive RR interval differences; LF, low-frequency; HF, high-frequency; LF/HF, LF/HF ratio; SD1, Poincaré plot standard deviation perpendicular the line of identity; SD2, Poincaré plot standard deviation along the line of identity.

Table 2. Intra-class correlation between heart rate variability (HRV) parameters obtained from Kubios HRV software and biofeedback device (BIO) at pre-exercise status.

Parameters	Mean ± standard deviation		Interclass correlation		
	Kubios HRV	BIO	ICC	95% CI	*P*
RR intervals (ms)	6.63 ± 0.11	6.65 ± 0.11	0.780*	0.630–0.869	< 0.001
SDNN (ms)	3.38 ± 0.41	3.42 ± 0.33	0.874*	0.779–0.928	< 0.001
RMSSD (ms)	2.75 ± 0.42	2.88 ± 0.42	0.769*	0.598–0.868	< 0.001
PNN50 (%)	37 ± 1.080	0.74 ± 1.56	0.612*	0.162–0.821	0.008
LF (ms^2)	5.46 ± 0.90	4.60 ± 0.56	0.641*	0.398–0.785	< 0.001
HF (ms^2)	4.24 ± 0.90	4.43 ± 0.67	0.722*	0.535–0.834	< 0.001
LF/HF ratio	0.26 ± 0.21	−0.431 ± 0.99	0.593*	0.319-–0.757	< 0.001
SD1	2.48 ± 0.52	2.26 ± 0.66	0.379*	−0.039–0.629	0.035
SD2	3.7 ± 0.57	4.20 ± 0.47	0.470*	0.112–0.683	0.008

* Significant observation.

3.2. Correlation and agreement between indices at post-exercise

At post-exercise status, the HRV parameters were measured using the BIO and ECG devices, which are presented in **Figure 2** and **Table 3**. Regarding the Pearson test, some HRV parameters had low correlations ($0.3 < r < 0.5$) to high correlations ($r = 0.779$), such as RR interval ($r = 0.496$, $p < 0.001$), LF ($r = 0.260$, $p < 0.05$), HF ($r = 0.369$, $p < 0.01$), LF/HF ratio ($r = 0.394$, $p < 0.01$), and SD2 ($r = 0.299$, $p < 0.05$) (**Figure 2**). Regardless, other HRV parameters did not show any relationships between BIO and ECG at post-exercise conditions, including SDNN ($r = 0.099$, $p = 0.451$), RMSSD ($r = 0.118$, $p = 0.369$), PNN50 ($r = 0.135$, $p = 0.548$), and SD1 ($r = 0.117$, $p = 0.372$) (**Figure 2**). Similarly, based on intra-class correlation coefficient (ICC) analysis, some HRV indices obtained from these measurement devices illustrate a considerable agreement between BIO and ECG, ranging from low (below 0.50) to moderate (0.50 to 0.75), including RR intervals (ICC = 0.623, $p < 0.001$), HF (ICC = 0.553, p = 0.001), and LF/HF ratio (ICC = 0.506, $p < 0.001$), while LF (ICC = 0.438, $p < 0.014$) and SD2 (ICC = 0.394, $p = 0.028$) had a slight correlation (**Table 3**). Despite this, no agreements were noted among other indices, including SDNN (ICC = 0.180, $p = 0.224$), RMSSD (ICC = 0.172, $p = 0.235$), PNN50 (ICC = 0.212, $p = 0.295$), and SD1 (ICC = 0.178, $p = 0.228$) (**Table 3**).

Table 3. Intra-class correlation between heart rate variability (HRV) parameters extracted via Kubios HRV and biofeedback device (BIO) at post-exercise status.

Parameters	Mean ± SD		Interclass correlation		
	Kubios HRV	BIO	ICC	95% CI	*P*
RR intervals (ms)	6.21 ± 0.09	6.38 ± 0.14	0.623*	0.35–0.776	<0.001
SDNN (ms)	4.39 ± 0.38	4.06 ± 0.41	0.180	−0.373–0.510	0.224
RMSSD (ms)	2.20 ± 0.5	3.35 ± 1	0.172	−0.386–0.506	0.235
PNN50 (%)	−0.12 ± 0.98	1.05 ± 1.60	0.212	−0.899–0.673	0.295

Table 3. (*Continued*).

Parameters	Mean ± SD		Interclass correlation		
	Kubios HRV	BIO	ICC	95% CI	*P*
LF (ms^2)	3.73 ± 1.3	4.20 ± 0.92	0.394*	−0.015–0.638	0.028
HF (ms^2)	2.56 ± 1.45	4.33 ± 1.12	0.553*	0.252–0.733	0.001
LF/HF ratio	1.16 ± 1	−0.13 ± 0.57	0.506*	0.173–0.705	<0.001
SD1	1.9 ± 0.59	2.75 ± 1.11	0.178	−0.377–0.509	0.228
SD2	4.71 ± 0.3	4.69 ± 0.43	0.438*	−0.060–0.664	0.014

* significant observation.

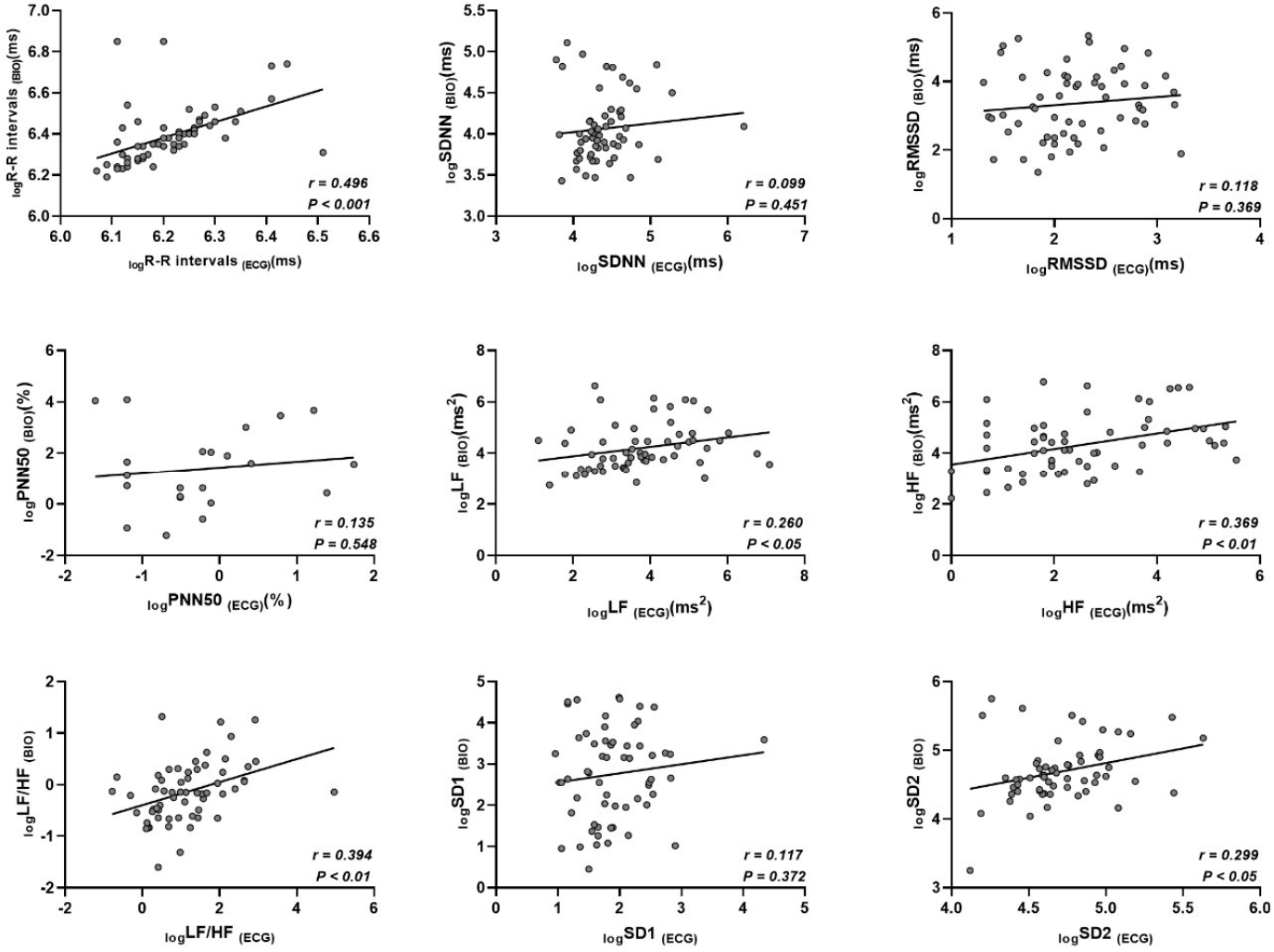

Figure 2. Pearson correlations between heart rate variability (HRV) parameters extracted via Kubios HRV and biofeedback device at post-exercise status. Abbreviations: BIO, the biofeedback device; ECG, the electrocardiogram device; SDNN, Standard deviation of NN intervals; RMSSD, Root mean square of successive RR interval differences; LF, low-frequency; HF, high-frequency; LF/HF, LF/HF ratio; SD1, Poincaré plot standard deviation perpendicular the line of identity; SD2, Poincaré plot standard deviation along the line of identity.

4. Discussion

Based on our knowledge, our research is the first study to have assessed the HRV measurement among healthy individuals by biofeedback, which means it

demonstrated the significant correlation between ECG (as the golden-standard method) and biofeedback, especially at pre-exercise status. Therefore, this is the first time that HRV-bio is considered a swift real-time method for monitoring HRV among a healthy population before and after a physical activity performance (i.e., MEP).

HRV is known as a productive way to understand the cardiovascular response in the human body [96]. Healthy heart oscillations are constantly changing, which helps the cardiovascular system adjust rapidly to any homeostasis challenges (either physical or psychological) [1,96]. HRV has assessed the neuro-cardiac function, which shows the direct relation between cardiac rhythm and the ANS branches, including the sympathetic and parasympathetic systems [97]. Therefore, HRV represents an emergent property of interdependent regulating systems, which provide various time scales to respond to any psycho-environmental challenges [98]. In healthy individuals, it reflects the satisfied regulation of different items in the body, such as autonomic balance, blood pressure, gas exchange, gut, heart, and vascular tone [81], while any diseases would involve either a decrease or elevation in the complexity of the biological system [99]. Recently, De Groot et al. have declared that ANS dysregulation symptoms are associated with diabetes-related distress among adults suffering from type 1 diabetes [100]. As a result, close monitoring of electrocardiogram (ECG) morphology would declare that increased HRV values are due to common cardiovascular conditions, including hypertension, diabetes mellitus, myocardial infraction, and heart failure [101,102], atrial fibrillation [103], and an early indication of infection [104,105]. Pathologically, clinical-dependent bradycardia could stem from vagal tone withdrawal (i.e., parasympathetic activity reduction), which causes the cardiac pacemaker to be more vulnerable to sympathetic impacts [106].

On the other hand, HRV indices are beneficial far beyond clinical prediction, which are considerably strong biomarkers to monitor physiological activity and workout levels [57,96]. Therefore, it can be applied to evaluate the level of exercise stress, especially the acute intensity by changes of the ANS following any exercise, which means it would be considered either overtraining or an overreaching marker [107,108]. Based on the PNS activity of every individual, monitoring HRV would be used to check individualized training improvement [109]. It has been illustrated that guided training based on HRV is a beneficial way to improve performance [109]. Being exposed to any physical stressor lessens HRV, which occurs as a result of vagal tone withdrawal and activating the sympathetic nervous system for supplying any exercises and physical activities' demands [108].

It is noted that an increased LF/HF ratio promotes cognitive performance [110], which is known as various strict internal operations reflected by behavior [111], while it is discovered that lessened vagal control (especially HF) is related to reduced ability of dynamical response to changing demands and environments, followed by the reduction of possible options' range and the limitation of an individual's ability to produce suitable responses and prevent inappropriate ones [112]. Likewise, it has been demonstrated that a low HRV is related to poorer performance associated with short- and long-term verbal memory [113]. If executive functioning is required for a cognitive task, therefore, vagal withdrawal is considered maladaptive [114], while it would be advantageous whenever a person is subjected to any mental stressors without including executive function, which means it is demonstrated as an individual's ability

to deal with the stimulus successfully [115,116]. Moreover, it is expressed that cardiac vagal activity can be considered an index of self-regulatory and/or cognitive-related processing [117–119]. The study literature illustrates the necessity of monitoring HRV for both physical and mental purposes among healthy people via a swift real-time method.

ECG is a traditional method for measuring HRV, which requires time and expertise. Moreover, other devices are high-priced, including clinical multi-lead ECG (e.g., Holter), which would not be practical for field-based monitoring in active and healthy individuals. Although multi-lead ECG devices are considered the golden standard, devices based on single-lead ECG or photo-plethysmography (PPG) are simple to apply [57]. Applying PPG technology to measure HRV is a recent and novel method, which is integrated into wearable wrist and finger-worn devices. Despite the motion artifact noted as a limitation of this method, their comfort and feasibility make them attractive alternatives to multi-lead ECG systems [58].

Regarding our study, there is significant agreement between ECG and BIO devices for measuring HRV indexes among healthy individuals at rest conditions. To prove this, the RR interval had moderate correlation ($r = 0.639$, $p < 0.001$), good ICC ($r = 0.780$, $p < 0.001$), and an average deviation of −0.01593 ms according to the Bland-Altman plots (95% LoA: −0.1984 to 0.1665 ms). As for SDNN, it showed high agreement ($r = 0.779$, $p < 0.001$), acceptable ICC ($r = 0.874$, $p < 0.001$), and an average deviation of −0.03843 ms according to the Bland-Altman plots (95% LoA: −0.5041 to 0.5664 ms). Also, RMSSD noted moderate correlation ($r = 0.625$, $p < 0.001$), good ICC ($r = 0.769$, $p < 0.001$), and an average deviation of −0.1465 ms according to the Bland-Altman plots (95% LoA: −0.8594 to 0.5664 ms). Plus, LF noted moderate correlation ($r = 0.524$, $p < 0.001$), low ICC ($r = 0.641$, $p < 0.001$), and an average deviation of −0.8597 ms^2 according to the Bland-Altman plots (95% LoA: −0.6665 to 2.386 ms^2). In addition, as for HF, it showed moderate agreement ($r = 0.589$, $p < 0.001$), good ICC ($r = 0.722$, $p < 0.001$), and an average deviation of −0.1835 ms^2 according to the Bland-Altman plots (95% LoA: −1.644 to 1.277 ms^2). Despite this, PNN50 illustrated low correlation ($r = 0.455$, $p < 0.05$), moderate ICC ($r = 0.612$, $p = 0.008$), and an average deviation of −0.8882% according to the Bland-Altman plots (95% LoA: −3.386 to 1.609%). In addition, as for the LF/HF ratio, it showed moderate agreement ($r = 0.559$, $p < 0.001$), good ICC ($r = 0.593$, $p < 0.001$), and an average deviation of 0.2213 according to the Bland-Altman plots (95% LoA: −0.1381 to 0.5808). Despite this, SD2 illustrated low correlation ($r = 0.313$, $p < 0.05$), low ICC ($r = 0.47$, $p = 0.008$), and an average deviation of −0.4317 according to the Bland-Altman plots (95% LoA: −1.645 to 0.7821), while SD1 illustrated no correlation ($r = 0.241$, $P = 0.064$), low ICC ($r = 0.379$, $p = 0.035$), and an average deviation of 0.2155 according to the Bland-Altman plots (95% LoA: −1.244 to 1.675) (**Figure 3**). On the other hand, at post-exercise status, the RR interval had low correlation ($r = 0.496$, $p < 0.001$), moderate ICC ($r = 0.623$, $p < 0.001$), and an average deviation of −0.1785 ms according to the Bland-Altman plots (95% LoA: −0.4270 to 0.07008 ms). As for SDNN, it did not show agreement ($r = 0.099$, $p = 0.451$), ICC ($r = 0.180$, $p = 0.224$), and had an average deviation of 0.3343 ms according to the Bland-Altman plots (95% LoA: −0.7245 to 1.393 ms). Also, RMSSD did not note any correlation ($r = 0.118$, $p = 0.369$), and ICC ($r = 0.172$, $p = 0.235$) had an average deviation of −1.150 ms

according to the Bland-Altman plots (95% LoA: −3.254 to 0.9540 ms). Whereas LF noted low correlation (r = 0.260, p < 0.05), low ICC (r = 0.438, p < 0.014), and an average deviation of −0.4675 ms^2 according to the Bland-Altman plots (95% LoA: −3.195 to 2.260 ms^2). In addition, as for HF, it showed low agreement (r = 0.369, p < 0.01), moderate ICC (r = 0.553, p = 0.001), and an average deviation of −1.772 ms^2 according to the Bland-Altman plots (95% LoA: −4.602 to 1.059 ms^2). Despite this,

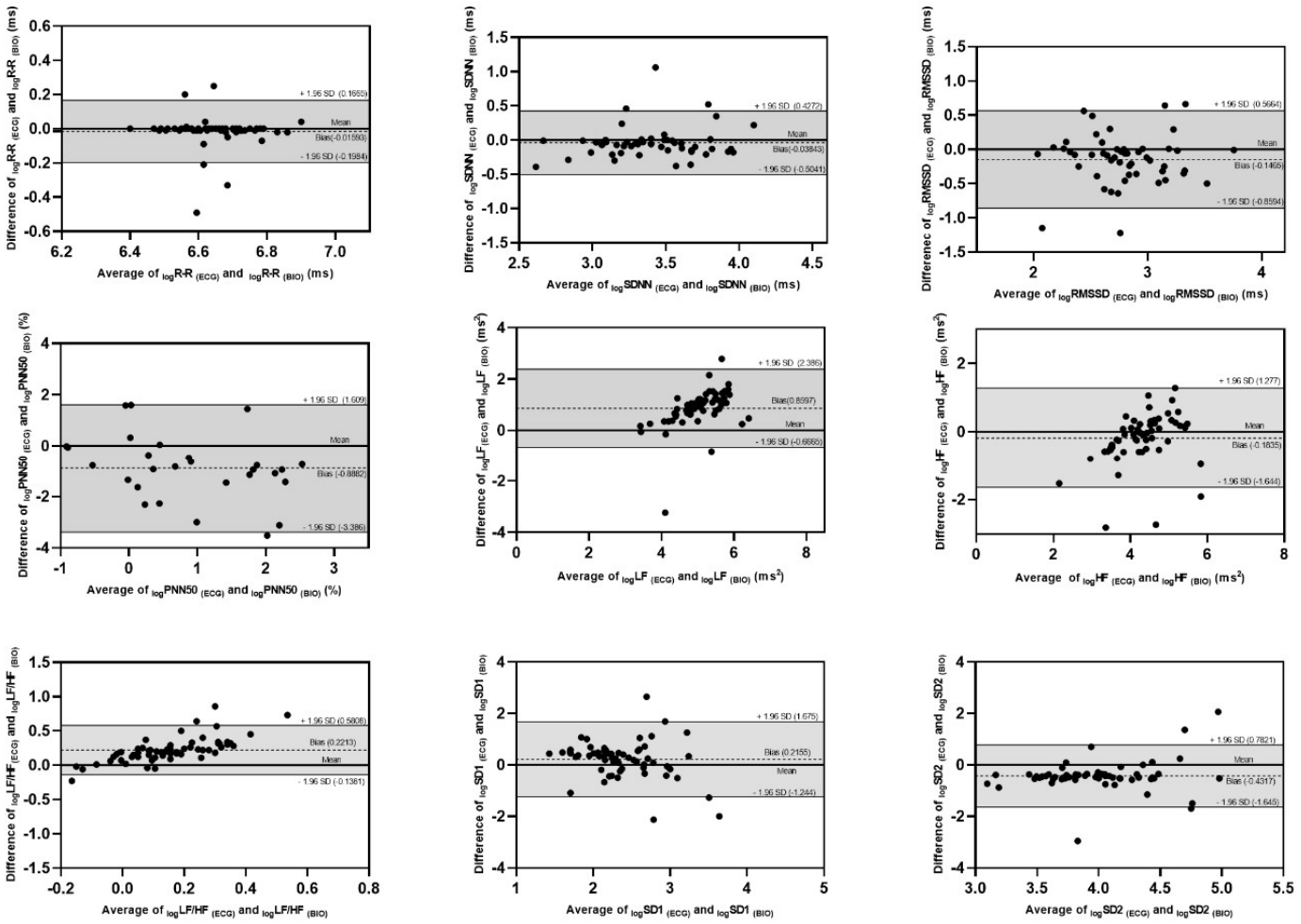

Figure 3. Bland-Altman plots of heart rate variability (HRV) parameters extracted via Kubios HRV and biofeedback device at pre-exercise status. Abbreviations: BIO, the biofeedback device; ECG, the electrocardiogram device; SDNN, Standard deviation of NN intervals; RMSSD, Root mean square of successive RR interval differences; LF, low-frequency; HF, high-frequency; LF/HF, LF/HF ratio; SD1, Poincaré plot standard deviation perpendicular the line of identity; SD2, Poincaré plot standard deviation along the line of identity.

PNN50 did not illustrate correlation (r = 0.135, p = 0.548), moderate ICC (r = 0.212, p = 0.295), and an average deviation of −1.603% according to the Bland-Altman plots (95% LoA: −4.926% to 1.720%). As for LF/HF ratio, it showed low agreement (r = 0.394, p < 0.01), moderate ICC (r = 0.506, p < 0.001), and an average deviation of 1.305 according to the Bland-Altman plots (95% LoA: −0.5411 to 3.151). Despite this, SD2 illustrated low correlation (r = 0.299, p < 0.05), low ICC (r = 0.394, p = 0.028), and an average deviation of 0.02067 according to the Bland-Altman plots (95% LoA: −0.8621 to 0.9035), while SD1 illustrated no correlation (r = 0.117, p = 0.372), ICC

(r = 0.178, p = 0.228), and an average deviation of −0.8513 according to the Bland-Altman plots (95% LoA: −3.201 to 1.498) (**Figure 4**). Therefore, not only is a biofeedback device considered an effective method for monitoring autonomic balance [12,74], but it can also be applied among healthy individuals regarding our study, especially at pre-exercise status.

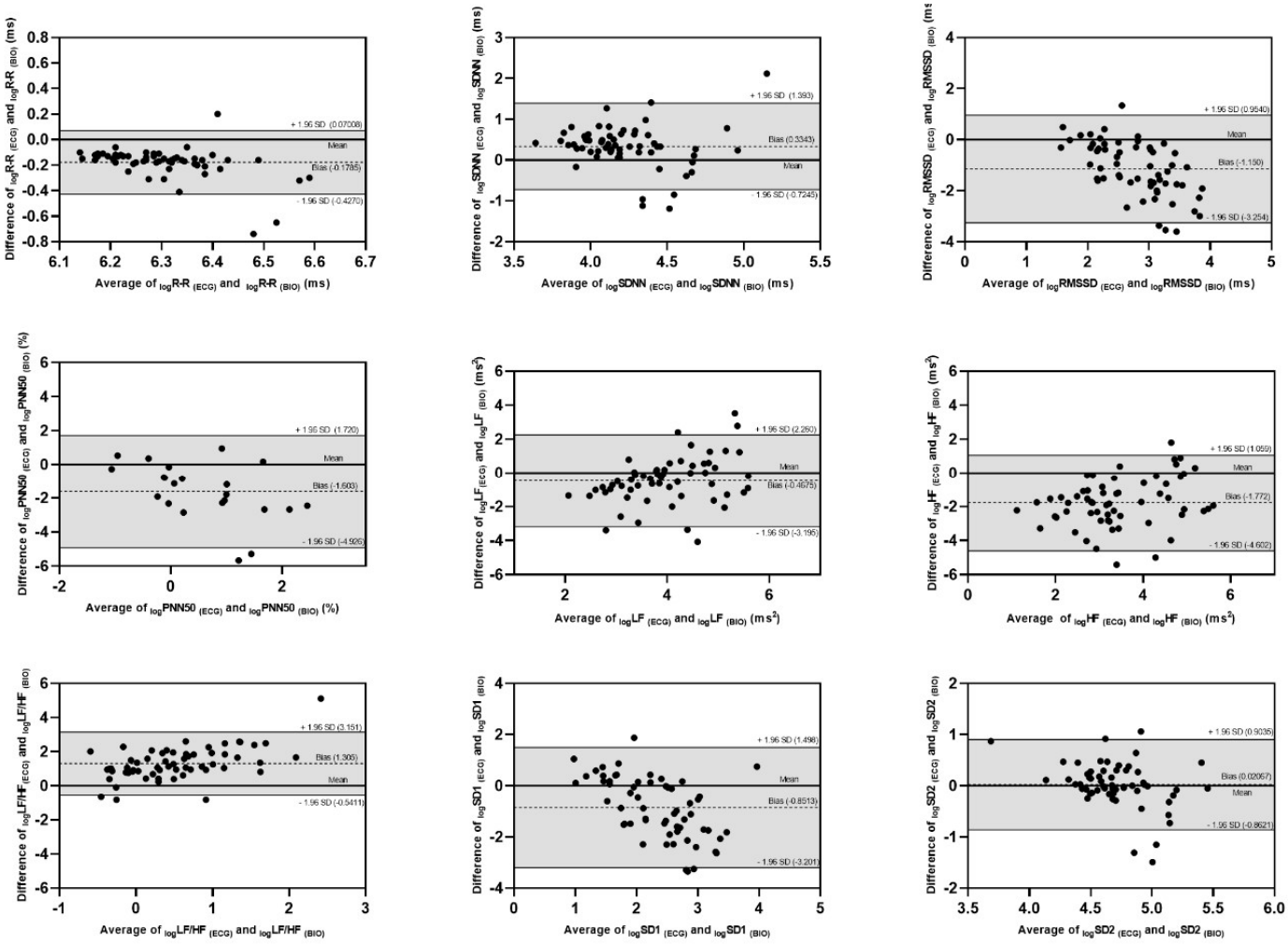

Figure 4. Bland-Altman plots of heart rate variability (HRV) parameters extracted via Kubios HRV and biofeedback device at post-exercise. Abbreviations: BIO, the biofeedback device; ECG, the electrocardiogram device; SDNN, Standard deviation of NN intervals; RMSSD, Root mean square of successive RR interval differences; LF, low-frequency; HF, high-frequency; LF/HF, LF/HF ratio; SD1, Poincaré plot standard deviation perpendicular the line of identity; SD2, Poincaré plot standard deviation along the line of identity.

Altogether, this study showed a significant correlation between the golden method and the biofeedback device, which illustrates that the biofeedback device's usefulness is far beyond its clinical activities. Despite this, it should not be overlooked that we had some limitations in this study. Firstly, since the purpose of this paper was to assess whether biofeedback can be applied for HRV measurement among healthy people, we did not include athlete populations. Secondly, although the women were in the initial follicular phase of the menstrual cycle during the experiment period, the ovarian hormone levels were not measured directly. Finally, to prevent any possible noises being caused by body movement, we could not apply the biofeedback device

while performing MEP. Therefore, further studies are required to elucidate the impacts of these limitations while measuring HRV by biofeedback among healthy individuals.

5. Conclusion

Monitoring HRV in the population could be advantageous for tailoring individualized training and exercise programs according to the onset of illness or infection, identifying the risk of overreaching and overtraining, quantifying cognitive performance, and as an overall measure of health [31–49]. Regarding the preceding paragraphs, although the HRV_{ECG} is known as the golden method, it has several limitations [120,121], such as either expertise or time requirements, and good-quality electrode signals [122], which also prevents its applicability for prolonged-daily measurement [123]. Uniquely, this study states that biofeedback can be considered a facilitative way to evaluate HRV among healthy people, especially at pre-exercise status. Further research would be relevant for specific the HRV_{BIO} at different timelines of performing any exercises.

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Practical Implications (highlights): (1) A significant correlation was noted between HRV_{ECG} and HRV_{BIO}. (2) Biofeedback devices can be considered novel methodological tools to monitor the cardiovascular autonomic system before any physical activities and exercises. (3) Biofeedback devices can be applied for faster examination of HRV in healthy individuals.

Conflict of interest: The authors declare no conflict of interest.

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