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# Relationships between oxygen uptake, dynamic body acceleration and heart rate in humans

**Short title**: $VO_2$, acceleration and heart rate variability

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**Abstract**

Background: Accurate estimation of energy expenditure (EE) is important in human and animal behaviour analysis. Rate of oxygen consumption ($VO_2$) reflects EE during aerobic metabolism but is not always convenient. Alternative methods include heart rate (HR) and overall dynamic body acceleration (ODBA). A favourable ODBA-$VO_2$ relationship was recently reported but the strength of association between $VO_2$, ODBA, HR and its variability (HRV) is less clear.

Method: Fifteen young (23 ± 4 years) healthy males of similar aerobic fitness (maximal oxygen uptake, $VO_{2max}$ = 49.7±8.5 ml·kg$^{-1}$·min$^{-1}$) carried out progressive maximal exercise. ODBA, HRV and $\dot{V}O_2$ were recorded continuously. Relationships between ODBA, HRV and $\dot{V}O_2$ were explored using regression methods.

Results: $VO_2$ was strongly related to ODBA and RR during walking (R=0.45,0.30; $p<5x10^{-5}$) and running (R=0.60,0.38; $p<5x10^{-5}$). HRV was related to $VO_2$ during walking only (R=0.11-0.26; $0.005<p<5x10^{-5}$). A strong ODBA-RR relationship during walking (R=0.45; $p<5x10^{-5}$) was diminished during running (R=0.25; $p<5x10^{-5}$).

Conclusion: ODBA is a stronger proxy for EE than RR or HRV, especially during running gaits. HRV is weakly related to EE and cannot be recommended for its estimation. ODBA and RR are relatively easily measured but careful attention to gait is imperative as it changes these relationships markedly.

**1. Introduction**

Energy expenditure (EE) is directly linked to the effort of physical activity in animals and humans. It can therefore be used as an estimator of activity patterns in humans and of behaviour such as foraging and life history strategies in animals[1,2]. Proxies for EE, verified in humans and in a variety of animal species, include heart rate (HR)[3,4,5] and doubly-labelled water[6]. If the dominant energy supply is provided from aerobic metabolism (glycolysis) then EE can also be measured from respiratory gas analysis by quantifying the rate of oxygen uptake ($VO_2$) in the body[7,8]. Ambulatory gas analysis devices are available but these are relatively bulky and so are inappropriate for extended monitoring or for use with animals. In the main, previous methods for measuring energy expenditure are restrictive[9] and so more convenient methods have been sought.

One alternative method is provided by overall dynamic body acceleration (ODBA). ODBA provides strong predictive validity for $VO_2$ and for speed of motion[9-15]. Numerous studies have confirmed the relationship between ODBA and EE for animals and for humans walking on treadmills[8,10,16] and swimming[14,17,18]. In fact ODBA is linearly related to speed in animals but in humans the relationship is non-linear, owing to the change in gait (from walking to running) and the accompanying increase in vertical acceleration ('heave') that occurs at elevated speeds[10,19].

Although heart rate has also been used previously to estimate EE[5,6], the more sophisticated method of heart rate variability (HRV) has not. HRV is a measure of cardiac interval fluctuation, reflecting the autonomic neural regulation of heart rate that occurs on a beat-to-beat timescale. HRV is altered profoundly in response to physical activity: it declines continuously as energy expenditure increases with increasing workloads[20]. Since HR/HRV and ODBA are strongly related to both physical activity and $VO_2$ [20,21], all of these quantities should be substantively related, although quite how is unclear because no study has yet compared them[22]. Establishing the nature of these relationships might lead the way towards an improved or alternative predictor of EE. In particular, we propose that it is essential to examine how these relationships change according to the dominant locomotive gait (walking or running) in order to optimise their use during a wide range of dynamic motion.

The present study aimed to carry out these objectives in a new analysis of previously published ODBA data[21] obtained from individuals moving at different speeds and employing both walking and running gaits.

## 2. Methods

### 2.1 Subjects

The study protocol, methods of recruitment and procedures for obtaining and recording consent were approved by Swansea University's Applied Sport Technology Exercise and Medicine (A-STEM) Ethics Committee. Potential participants were informed in writing about the nature and requirements of the study, and those who agreed to take part gave written consent for participation. The study was conducted with adherence to the Declaration of Helsinki. Fifteen males (age 23 ± 4 years, mass 70.6 ± 10.1 kg [mean ± SD]) volunteered to take part in the investigation. Individual maximal oxygen uptake ($VO_{2max}$) values confirmed the homogeneity of aerobic fitness within the group (49.7 ± 8.5 $ml \cdot kg^{-1} \cdot min^{-1}$). Participant health screening was undertaken using the American Heart Association/ American College of Sports Medicine pre-participation screening questionnaire. All subjects were apparently healthy non-smokers and were physically active to a similar level. Subjects were free of cardiovascular and chronic respiratory problems, had no history of sleep apnoea, central or peripheral nervous system disorder, and were not taking any medication at the time of the study. Participants were asked to arrive at the laboratory in a rested and fully hydrated state at least two hours postprandial and to have avoided consuming caffeinated drinks for 24 hours prior to the test. No physical exercise was permitted in the 24 hour period prior to the assessment.

### 2.2 Exercise testing protocol

All measurements were carried out in a laboratory between 14h00 and 18h00. The protocol commenced with the participants lying supine for three minutes, after which they were asked to stand and remain stationary for three minutes. Following this, participants then immediately performed a progressive maximal exercise test on a treadmill (Woodway Ergo ELG 55, Woodway GMBH, Weil AM Rhein, Germany). The exercise test was performed with no inclination set on the treadmill and started at 3 km·hour$^{-1}$, increasing by 1·km hour$^{-1}$ every three minutes until the participant reached volitional exhaustion.

## 2.3 Physical measurements

Acceleration was measured using tri-axial accelerometers (X6-1A USB; Gulf Coast Data Concepts, LLC, Waveland, USA; 16 bit resolution, recording range -6 to 6 g), each set to record at 80 Hz on each of the three orthogonal axes. The accelerometer data loggers were placed within holding moulds cut into a single polystyrene saddle to ensure correct orientation in accordance with the main body axes of 'surge', 'heave' and 'sway'. The saddle was optimised (by trial and error during pilot studies) to move properly with the participant's body. It was placed in the centre of the participant's back between the shoulder blades and held in place using a specially made harness that kept the system in a stable position even during vigorous movement (Figure 1(a)).

Figure 1 here

A Reynolds Lifecard CF digital Holter recorder (Spacelabs Medical Ltd., UK) was used to record a three-lead ECG continuously throughout the pre-exercise, exercise and post-exercise periods. The ECG leads were positioned in the 'modified V5, CC5, modified V5R' electrode configuration (as recommended by Spacelabs Medical Ltd.) (Figure 1(b)). This system provided ECG data with a sample accuracy of 2.5 µV (12-bit resolution) and 1024 Hz sampling frequency. We performed all analyses using data from a single ECG lead (Lead 1 for each subject). The ECG recordings were analysed using a Reynolds Pathfinder digital analyser (Spacelabs Medical Ltd., UK). All ECG data used for subsequent analysis in this study were free of any form of morphologically abnormal beat, and this was verified by both the Holter system and by human observation. Beat-to-beat cardiac interval (RR) data were automatically measured for each sinus beat and exported for further analysis using the Reynolds Research Tools software (Spacelabs Medical Ltd., UK). The RR data also underwent human visual examination in order to verify the accuracy of the data prior to subsequent analysis. When either the RR intervals were considered to be anomalous these data points were removed from the data set. This occurred infrequently (and mainly during exercise), resulting overall in less than 1% of the data being removed. (We use RR hereafter rather than the derived measure HR (where HR=60/RR) to indicate cardiac cycle duration.)

Breath-by-breath respiratory data were recorded throughout using an Oxycon Pro respiratory gas analysis system (Carefusion, Hampshire, UK) to enable estimation of subjects' aerobic capacity (from $VO_2$, the rate of uptake of oxygen by the body) (Figure 2).

Figure 2 here

2.5 Data analysis

Instantaneous ODBA values were calculated from the raw triaxial accelerometer signal according to the method described by Halsey and White[13], using a running mean over two seconds to derive the static portion of the signal[22]. This static component was subtracted from the total acceleration in order to obtain the dynamic component. The absolute dynamic components for all three axes were then summed to obtain instantaneous ODBA. Mean values of ODBA were determined over one-minute periods throughout the exercise test for each participant.

HRV parameters were quantified in the time and frequency domains using bespoke software (‘HRV Analysis’, SwanSTEM Limited, Swansea, UK) according to the Task Force guidelines on HRV[23]. The following variables were calculated: ‘RMSSDRR’, the square root of the mean of the sum of the squares of differences between adjacent RR intervals; ‘SDRR’, the standard deviation of all RR intervals; ‘Total Power’, in the bandwidth 0.017 to 0.4 Hz; ‘Low Frequency (LF) Power’, in the bandwidth 0.04 to 0.15 Hz; ‘High Frequency (HF) Power’, in the bandwidth 0.15 to 0.4 Hz). Time domain variables were quantified using the raw (unevenly sampled) RR time-series. Prior to the frequency domain analysis procedures RR interval data were re-sampled using a sampling frequency of 2 Hz and then linearly de-trended and Hanning windowed in consecutive one-minute segments; the power spectral density of each segment was then calculated using the Welch periodogram method, using short-term Fourier transformation and a 50% overlap between adjacent segments.

2.6 Statistical analysis

The Lilliefors test was used to assess the Normality of the individual variables and, if necessary, log-transformation was used to improve the Normality of these data. Linear regression models were used to explore the relationships between $VO_2$ and ODBA, $VO_2$ and HR/HRV, and ODBA and HR/HRV for the participant group. Stepwise multiple linear regression analysis was used to assess the influence of combinations of HRV variables on the ODBA prediction model. Data are presented as Mean ± SEM (standard error of the mean).



**3. Results**

All participants showed consistent RR, ODBA and $VO_2$ time-series trends and similar HRV time-frequency plots as functions of increasing exercise workload (Figure 3). Note the substantial change in the time-frequency plot (Figure 3(a)) that occurs between minutes 21 and 23. This coincides with a change from a walking to a running gait, as shown by the step change in the ODBA data (Figure 3(d)). However, there is no change in $VO_2$ during this period, the trend in $VO_2$ remaining linear throughout exercise (Figure 3(c)). $VO_2$, ODBA and most of the HRV variables were found not to be Normally distributed and so all variables were log-transformed prior to further analysis.

Figure 3 here

Figure 4 (a-e) presents $VO_2$ as functions of RR/HRV and ODBA variables for all exercise efforts, separately for walking and running gaits. The results of linear regression analysis of $VO_2$ as functions of RR/HRV and ODBA are shown in Table 1(a), separately for walking and running gaits. RR was moderately well correlated with $VO_2$ during walking ($R = 0.30$, $p<5x10^{-5}$) and running ($R=0.38$, $p<5x10^{-5}$). HRV variables were also related to $VO_2$ during walking ($R = 0.11$-$0.26$; $5x10^{-5}<p<0.005$) but only very weakly during running ($R = 0.01$-$0.08$, $0.003<p<0.29$). $VO_2$ was strongly related to ODBA during walking ($R = 0.45$, $p<5x10^{-5}$) and even more strongly during running ($R = 0.60$, $p<5x10^{-5}$). Using a stepwise multiple linear regression analysis we observed that there was no meaningful improvement in the regression models when the RR/HRV variables were used in various combinations. Notably we observed mean reductions of 32-44% and maximal reductions of 57-90% in the RR/HRV variables when moving from a walking to a running gait. In comparison, ODBA increased by 280% during this gait transition. Thus there was a substantial shift in the relationship between these quantities during the gait transition. Figure 4(f) presents ODBA as a function of RR for all exercise efforts: a strong ODBA-RR relationship during walking ($R=0.45$; $p<5x10^{-5}$) was observed but this was diminished during running ($R=0.25$; $p<5x10^{-5}$), as shown in Table 1(b).

Tables 1(a) and 1(b) here

Figure 4 here

## 4. Discussion

Exercise within the maximal range of workloads elicited two distinct gait patterns, as expected[10,19]: walking at lower speeds and running at higher speeds. We therefore analysed the ODBA-HRV relationship separately for the walking and running phases of the physical exercise test. We expected that elevated workloads would be accompanied by increases in $VO_2$ and heart rate and a reduction in HRV[20], and this was the case.

Gait pattern (walking and running) had a substantial influence on the relationships between $VO_2$, ODBA and RR/HRV. ODBA showed the strongest relationship with $VO_2$ during both gaits, and this was especially strong during running. Heart rate (measured as RR) tracked changes in $VO_2$ quite well during walking and running, but the relationship between HRV and $VO_2$ was significant (yet weak) only during walking. Composite HRV variables provided no meaningful improvement in the degree of association between HRV and $VO_2$. A strong relationship was observed between ODBA and RR during walking but this was diminished during running.

We confirmed earlier reports that ODBA is strongly related to energy expenditure[10,13,14,16-18], although our maximal R value of 60% for the ODBA - $VO_2$ relationship is much smaller than the 92% reported recently by Qasem et al.[21]. It is worth noting that Qasem et al appear to have quantified their ODBA - $VO_2$ relationships without separating the data into walking and running gaits, and the large difference in ODBA values for these two gaits is likely to have biased their regression analysis.

HRV variables were weakly related to $VO_2$ and provided no benefit over RR interval alone for estimating energy expenditure. One likely explanation for this is the substantial (exponential type) reduction in HRV that occurs during progressively increasing exercise intensities[20]. This reduction in HRV has been reported during moderate-to-high metabolic challenge[24] and can be seen clearly in the time- and frequency domains in Figures 2(a) and 2(b) from the 21st minute onwards. This reduced HRV represents an almost complete loss of plasticity (responsiveness) in cardiac autonomic control and is a recognised confounder to the use of HRV at elevated workloads. If we consider that the measurement of both HRV and ODBA is associated with uniform measurement error then the relative accuracy of HRV calculation is diminished during running (when HRV is low), whilst for ODBA it is improved. Thus the poorer accuracy in quantifying HRV relative to ODBA is likely to have degraded the ODBA-HRV relationship during running.

Of the measured variables only ODBA and RR (or heart rate) can be used as surrogates of energy expenditure, and ODBA appears to be superior. This means that the often cumbersome evaluation of $VO_2$ might be avoided in situations such as field measurement or when the use of a respiratory facemask is not desirable or practical. This might be important in various situations: provided that either ODBA or RR can be quantified it would be possible to use these methods for the assessment of energy expenditure in animals in their natural environments (including under water), and in humans during the activities of daily living. ODBA and RR are relatively straightforward to administer and their use in predicting energy expenditure (and thus activity levels) could easily be incorporated into the analysis hardware/software of a personal monitor. There is a clear benefit of using either ODBA or RR as proxies for energy expenditure during sport and exercise – enabling physical activity and fitness levels to be quantified with small sensor systems that do not impede performance. There are clinical benefits too – for example, in assessing activity levels and aerobic fitness of individuals in their normal environments, and in quantifying the benefits of (and adherence to) treatments or rehabilitation programmes (such as oxygen therapy in chronic lung disease).

Somewhat surprisingly we found that the relationship between RR and ODBA was substantially weaker during running than during walking. This might have been caused by greater variation in either RR or ODBA (or both) whilst running, thus weakening the association between these variables. Further testing with larger populations will allow this to be investigated. We did not control for body mass when examining the relationships between ODBA, HRV and $VO_2$. We recognise that this would be useful in subsequent work, and that allometric scaling according to body mass might further improve the quantified relationships. Furthermore it might be expected that the $VO_2$ - ODBA - HRV relationships would differ to some extent in males and females, and so a more extensive study that quantifies gender-specific relationships will be needed.

In summary, ODBA and RR are relatively easily measured and are generally very good proxies for energy expenditure and thus physical activity levels. However, careful attention to gait is imperative during their measurement as gait changes these relationships markedly. Improved models relating ODBA and RR to energy expenditure and physical activity levels during different modes of exercise will further improve this potentially useful tool.

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**Figure legends**

Figure 1 (a) position of the accelerometer and harness and (b) Holter ECG and electrode placement

Figure 2 Respiratory gas collection using the Oxycon Pro system

Figure 3 (a) RR time-series and corresponding (b) HRV time-frequency plot, (c) ODBA time-series, (d) $VO_2$ for a single participant. (c),(d) show mean values for set exercise levels (treadmill velocities). (ODBA values are shown for minute 6 onwards as subjects were stationary up to this time.)

Figure 4 (a)-(e) Mean $VO_2$ as functions of mean RR/HRV and ODBA during walking and running gaits; (f) Mean ODBA as a function of mean RR during walking and running gaits

**Table 1(a)** Linear regression of $VO_2$ as functions of RR/HRV and ODBA during walking and running. (m = gradient and c = intercept of the regression line, p is the associated probability of no relationship between variables, r is the correlation coefficient and R = $r^2$.)

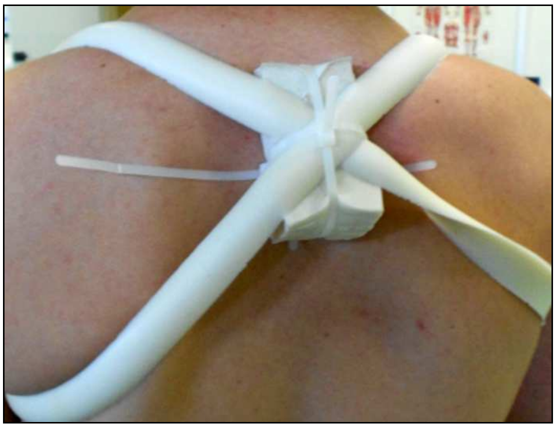
| Gait | Variable | m | c | p | r | R |
|---|---|---|---|---|---|---|
| Walking | | | | | | |
| | RMSSDRR | -0.169 | 0.595 | 0.005 | -0.33 | 0.11 |
| | SDRR | -0.236 | 0.894 | 0.002 | -0.37 | 0.14 |
| | LF | -0.226 | 0.421 | $<1x10^{-4}$ | -0.42 | 0.18 |
| | HF | -0.153 | 0.279 | 0.003 | -0.36 | 0.13 |
| | TP | -0.734 | 3.634 | $<5x10^{-5}$ | -0.51 | 0.26 |
| | RR | -0.958 | 6.220 | $<5x10^{-5}$ | -0.55 | 0.30 |
| | ODBA | 0.705 | -0.852 | $<5x10^{-5}$ | 0.67 | 0.45 |
| **Running** | | | | | | |
| | RMSSDRR | -0.026 | 1.108 | 0.293 | -0.11 | 0.01 |
| | SDRR | -0.042 | 1.150 | 0.090 | -0.17 | 0.03 |
| | LF | -0.038 | 1.039 | 0.033 | -0.21 | 0.04 |
| | HF | -0.023 | 1.045 | 0.216 | -0.12 | 0.02 |
| | TP | -0.240 | 2.101 | 0.003 | -0.29 | 0.08 |
| | RR | -1.125 | 7.710 | $<5x10^{-5}$ | -0.61 | 0.38 |
| | ODBA | 0.477 | 0.063 | $<5x10^{-5}$ | 0.78 | 0.60 |



**Table 1(b)** Linear regression of ODBA as a function of RR during walking and running.

| Gait | Variable | m | c | p | r | R |
|---|---|---|---|---|---|---|
| Walking | RR | -1.225 | 7.113 | $<5x10^{-5}$ | -0.67 | 0.45 |
| Running | RR | -0.462 | 6.201 | $<5x10^{-5}$ | -0.50 | 0.25 |

(a)



(b)


Figure 1 (a) position of the accelerometer and harness and (b) Holter ECG and electrode placement

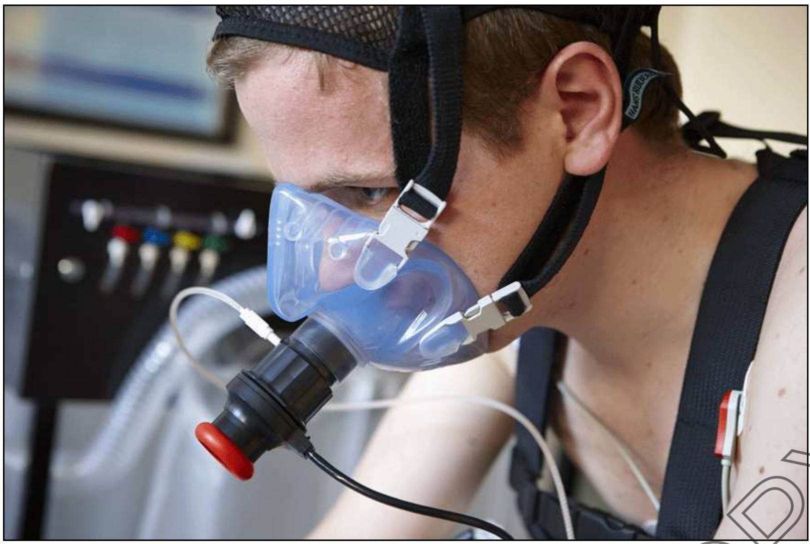


Figure 2 Respiratory gas collection using the Oxycon Pro system

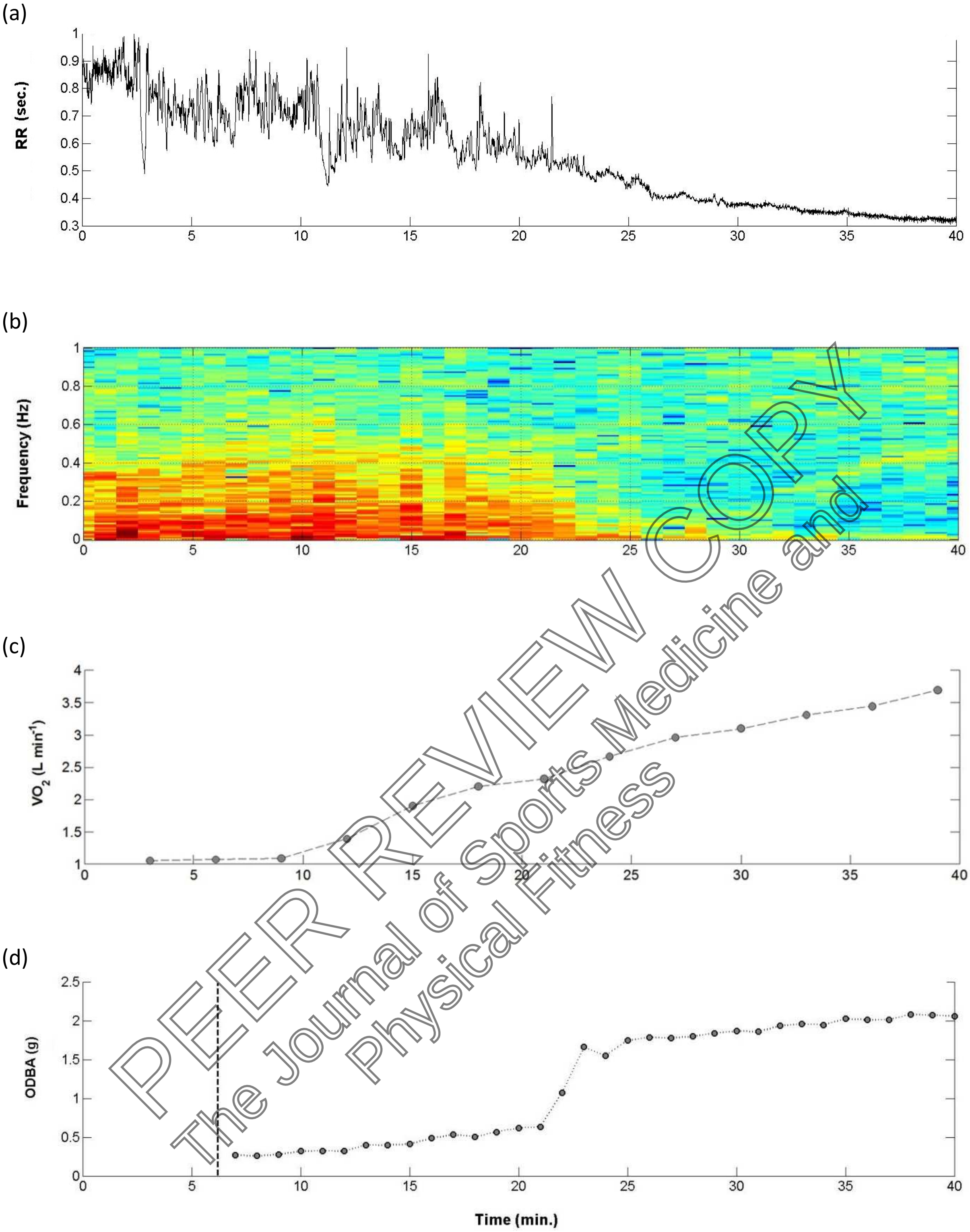



**Figure 3** (a) RR time-series and corresponding (b) HRV time-frequency plot, (c) ODBA time-series, (d) VO$_2$ for a single participant. (c),(d) show mean values for set exercise levels (treadmill velocities). (ODBA values are shown for minute 6 onwards as subjects were stationary up to this time.)

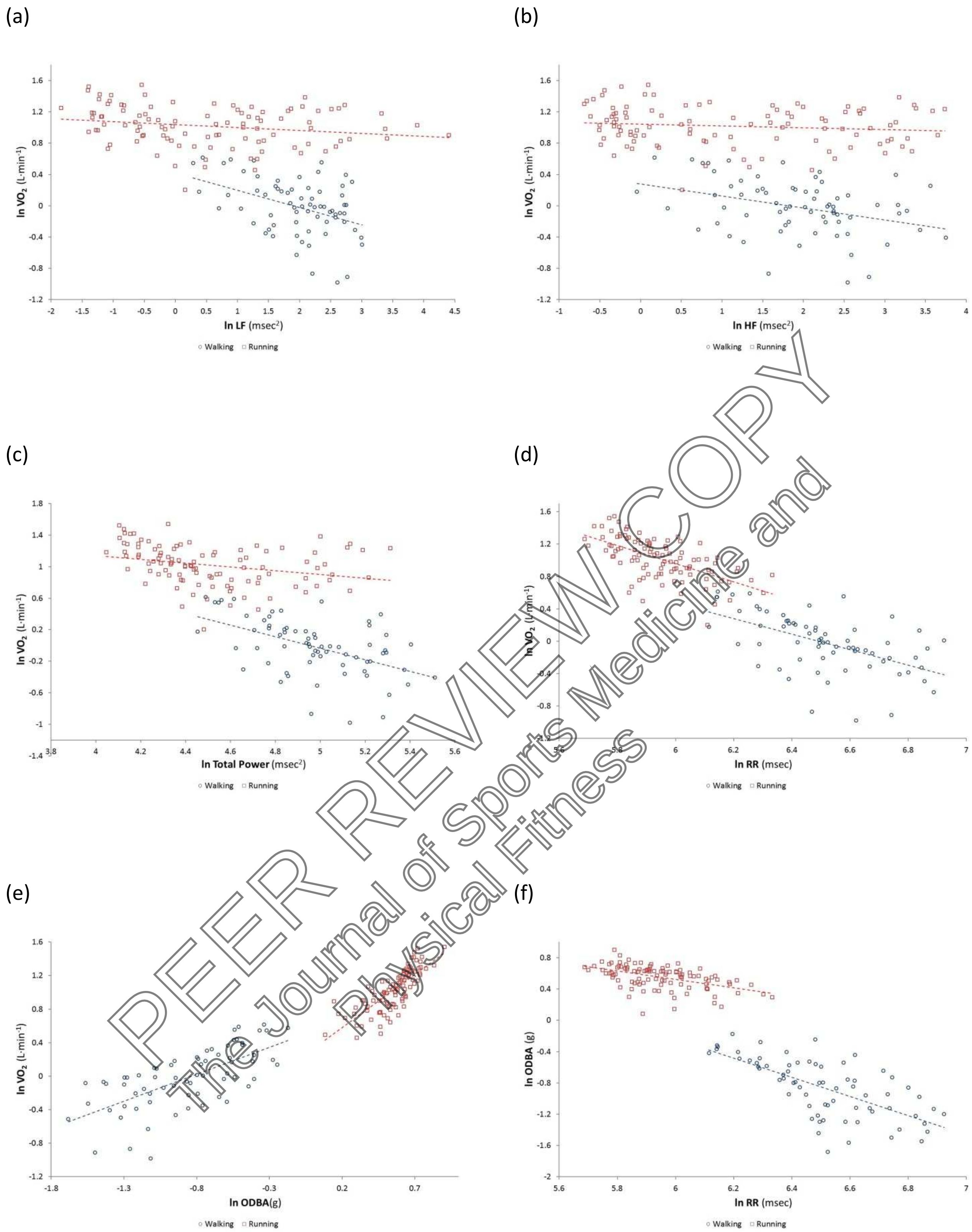



**Figure 4** (a)-(e) Mean $VO_2$ as functions of mean RR/HRV and ODBA during walking and running gaits; (f) Mean ODBA as a function of mean RR during walking and running gaits

**Table 1(a)** Linear regression of $VO_2$ as functions of RR/HRV and ODBA during walking and running. (m = gradient and c = intercept of the regression line, p is the associated probability of no relationship between variables, r is the correlation coefficient and R = $r^2$.)

| Gait | Variable | m | c | p | r | R |
|---|---|---|---|---|---|---|
| Walking | | | | | | |
| | RMSSDRR | -0.169 | 0.595 | 0.005 | -0.33 | 0.11 |
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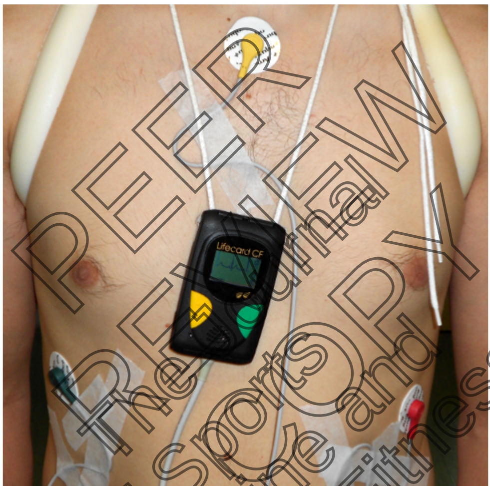
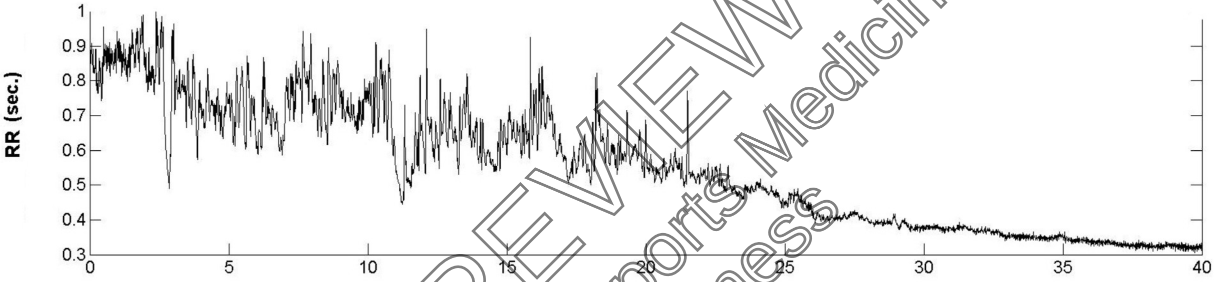
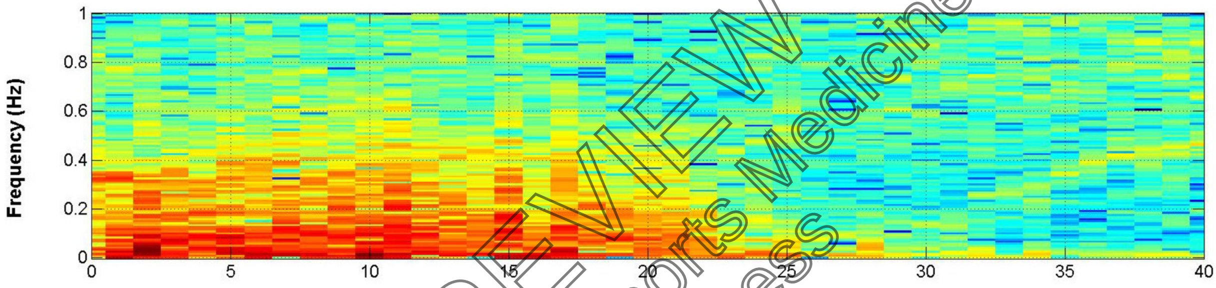
| **Running** | | | | | | |
| | RMSSDRR | -0.026 | 1.108 | 0.293 | -0.11 | 0.01 |
| | SDRR | -0.042 | 1.150 | 0.090 | -0.17 | 0.03 |
| | LF | -0.038 | 1.039 | 0.033 | -0.21 | 0.04 |
| | HF | -0.023 | 1.045 | 0.216 | -0.12 | 0.02 |
| | TP | -0.240 | 2.101 | 0.003 | -0.29 | 0.08 |
| | RR | -1.125 | 7.710 | $<5\times10^{-5}$ | -0.61 | 0.38 |
| | ODBA | 0.477 | 0.063 | $<5\times10^{-5}$ | 0.78 | 0.60 |

**Table 1(b)** Linear regression of ODBA as a function of RR during walking and running.

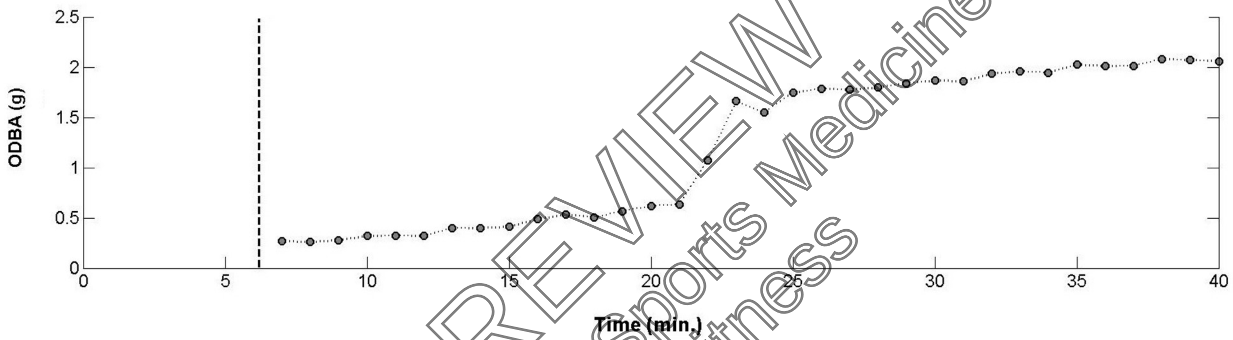
| Gait | Variable | m | c | p | r | R |
|---|---|---|---|---|---|---|
| Walking | RR | -1.225 | 7.113 | $<5x10^{-5}$ | -0.67 | 0.45 |
| Running | RR | -0.462 | 6.201 | $<5x10^{-5}$ | -0.50 | 0.25 |

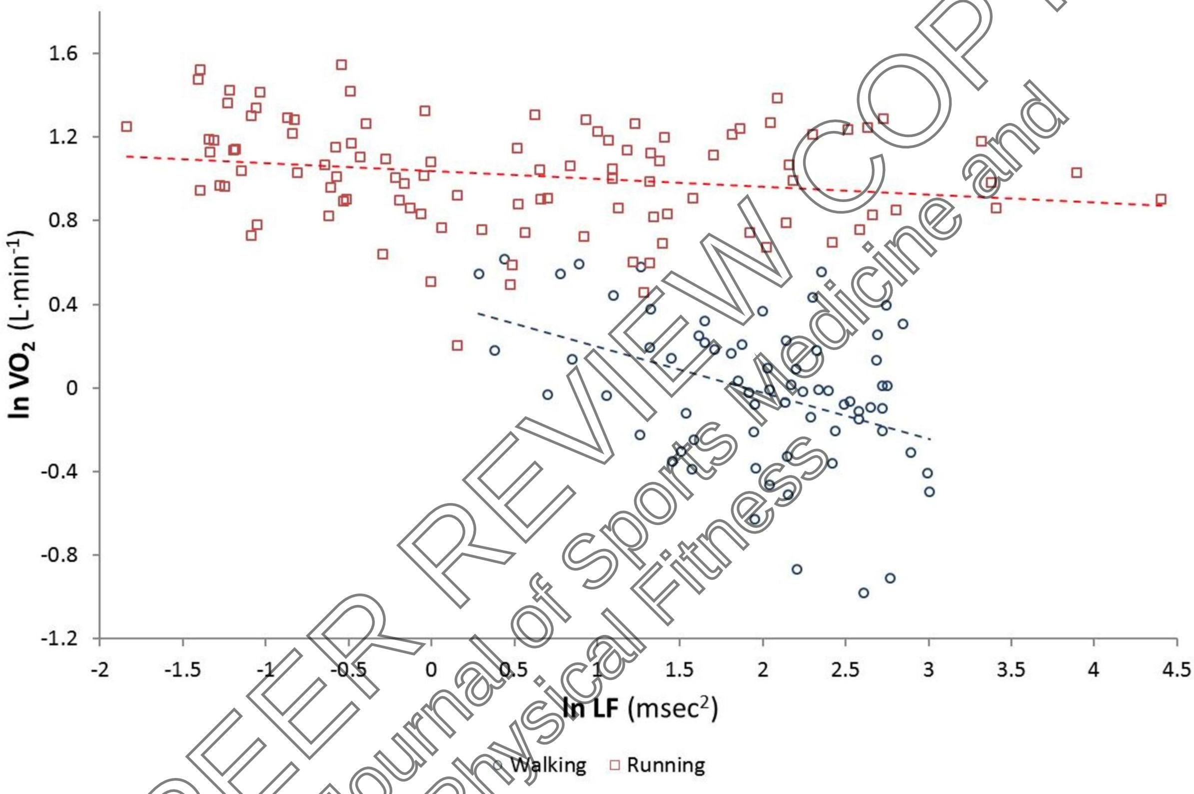

Lifecard CF

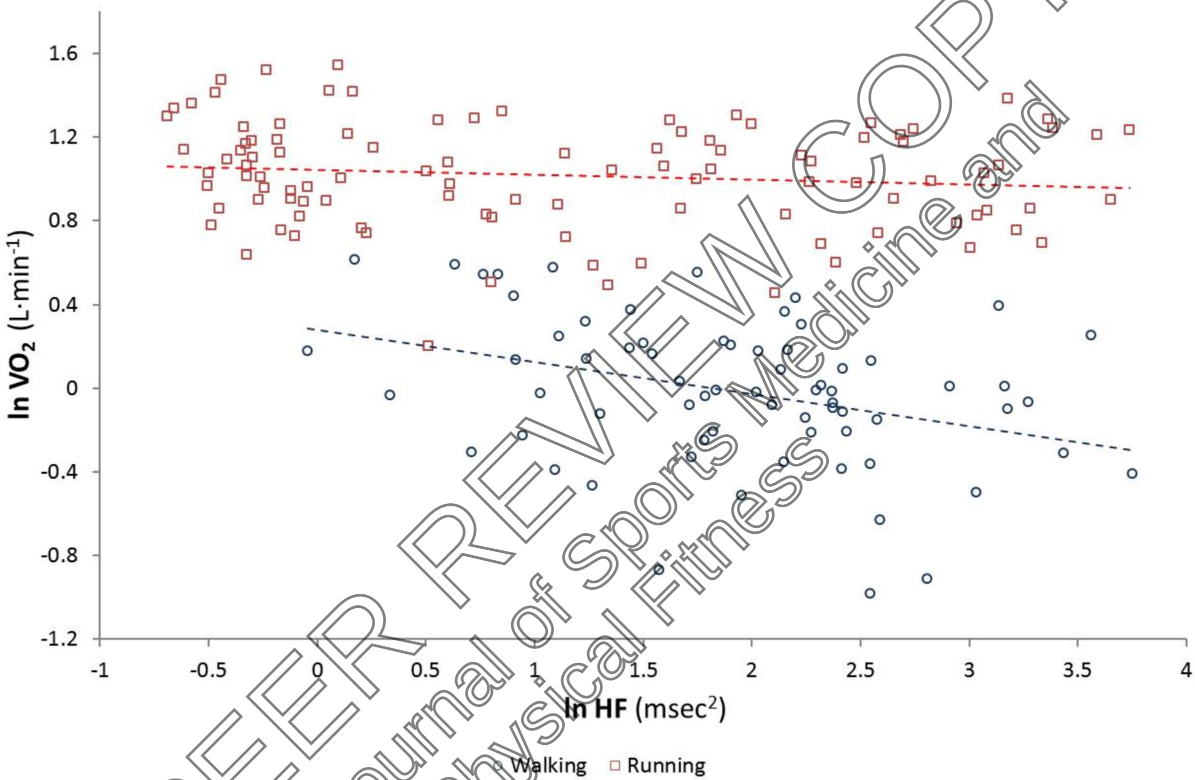

RR (sec.)
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0
5
10
15
20
25
30
35
40

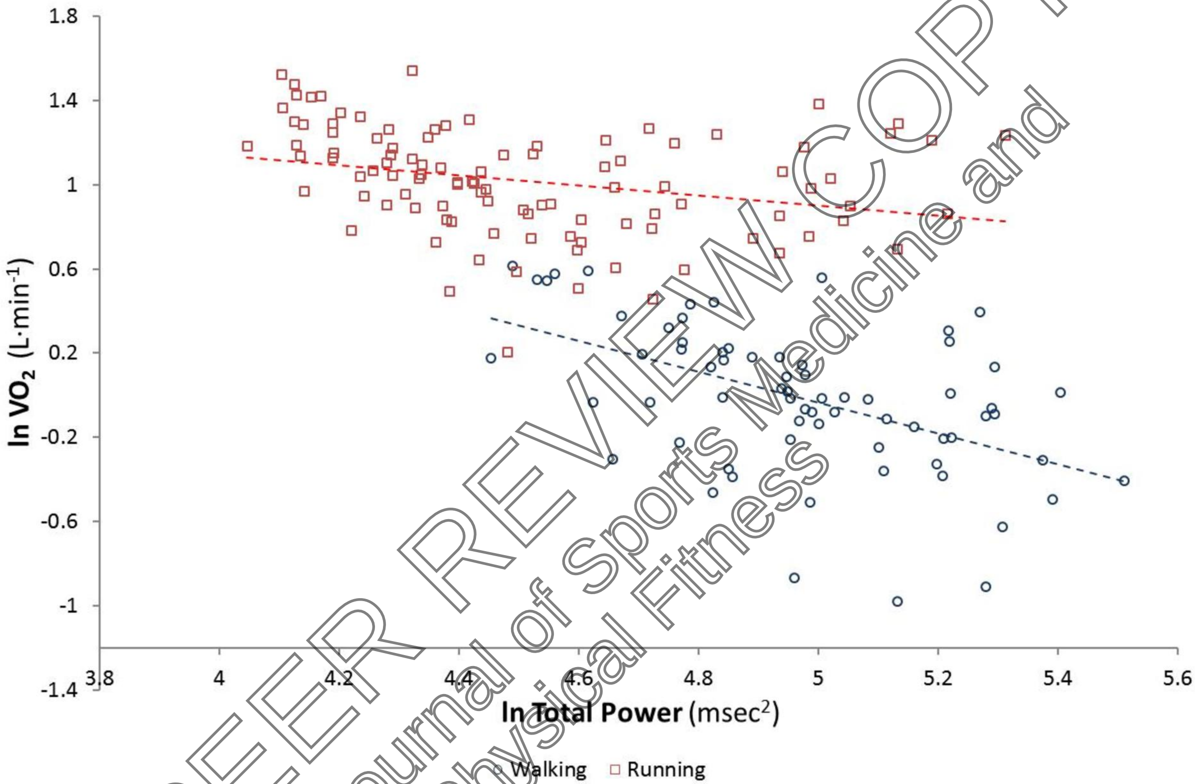

Frequency (Hz)
1
0.8
0.6
0.4
0.2
0
0
5
10
15
20
25
30
35
40

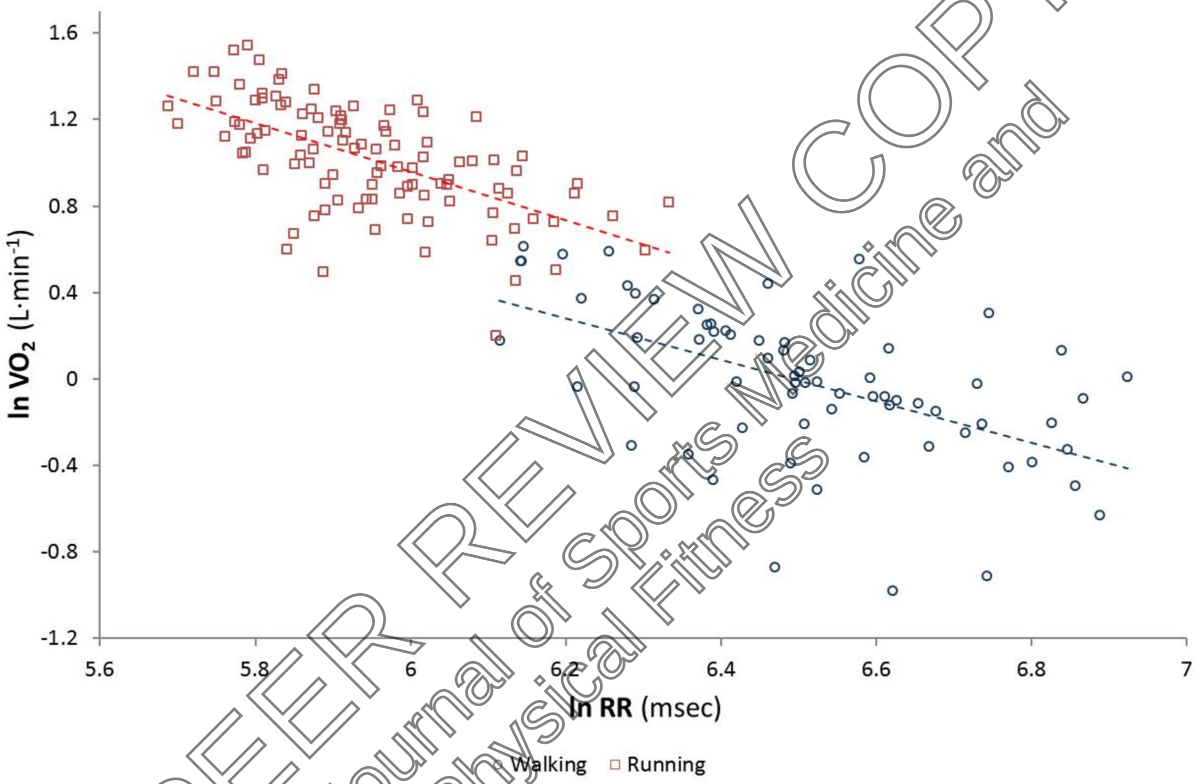

VO2 (L min-1)
4
3.5
3
2.5
2
1.5
1
0
5
10
15
20
25
30
35
40


ODBA (g)
2.5
2
1.5
1
0.5
0
0
5
10
15
20
25
30
35
40
Time (min.)

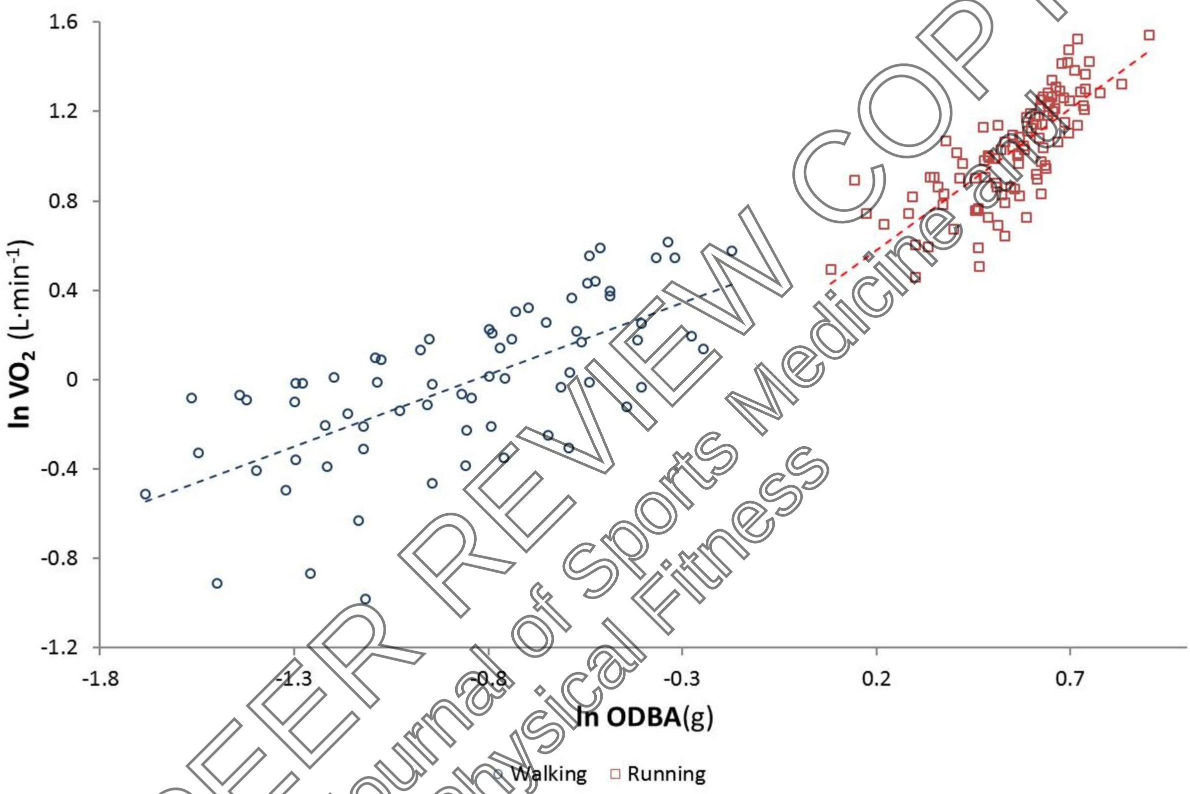

1.6
1.2
0.8
0.4
0
-0.4
-0.8
-1.2
ln VO2 (L·min-1)
-2
-1.5
-1
-0.5
0
0.5
1
1.5
2
2.5
3
3.5
4
4.5
ln LF (msec2)
Walking
Running

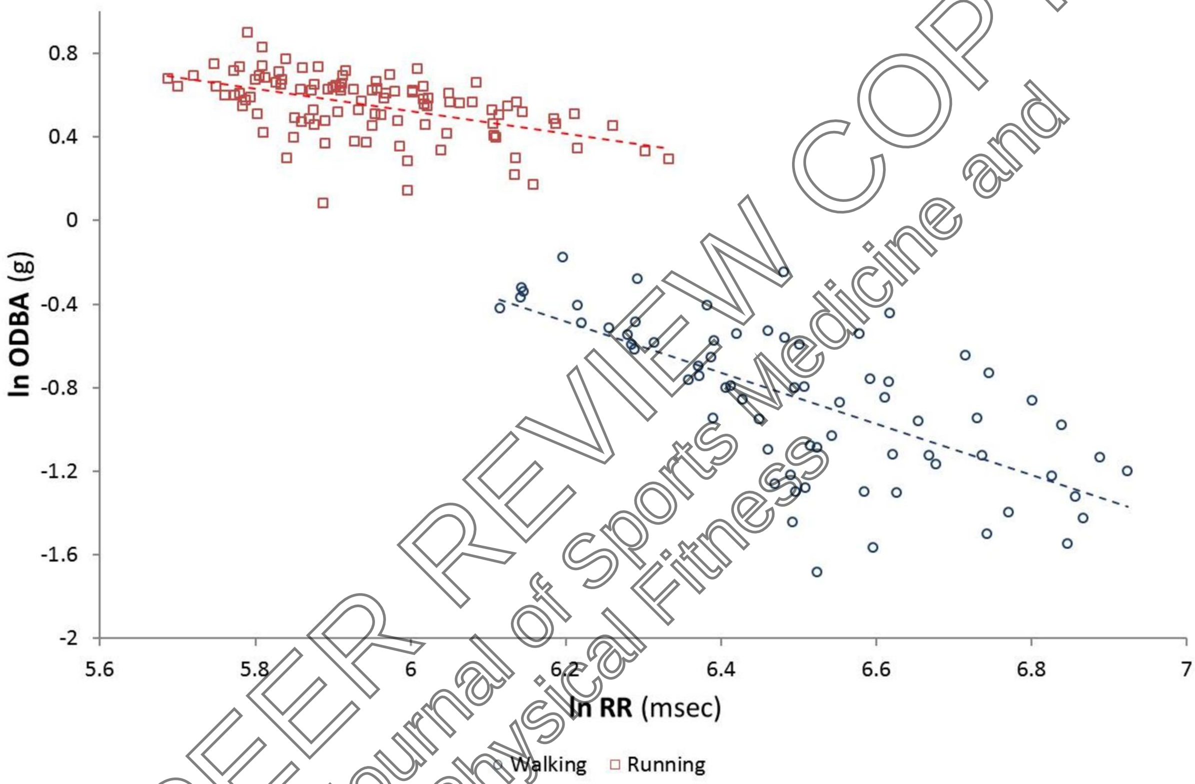

1.6
1.2
0.8
0.4
0
-0.4
-0.8
-1.2
-1
-0.5
0
0.5
1
1.5
2
2.5
3
3.5
4
ln VO2 (L·min-1)
ln HF (msec2)
Walking
Running


1.8
1.4
1
0.6
0.2
-0.2
-0.6
-1
-1.4
ln VO2 (L·min-1)
3.8
4
4.2
4.4
4.6
4.8
5
5.2
5.4
5.6
ln Total Power (msec2)
Walking
Running



1.6
1.2
0.8
0.4
0
-0.4
-0.8
-1.2
ln VO2 (L·min-1)
5.6
5.8
6
6.2
6.4
6.6
6.8
7
ln RR (msec)
Walking
Running


1.6
1.2
0.8
0.4
0
-0.4
-0.8
-1.2
ln VO2 (L·min-1)
-1.8
-1.3
-0.8
-0.3
0.2
0.7
ln ODBA(g)
Walking
Running


0.8
0.4
0
-0.4
-0.8
-1.2
-1.6
-2
ln ODBA (g)
5.6
5.8
6
6.2
6.4
6.6
6.8
7
ln RR (msec)
Walking
Running