ORIGINAL ARTICLE

# Estimation of energy expenditure in adults with accelerometry and heart rate

## Estimation de la dépense énergétique chez l'adulte par l'accélérométrie et fréquence cardiaque

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**Summary**
*Objectives.* — Accurate determination of energy expenditure (EE) through accelerometry is relevant in the effectiveness of the PA programs. The mean amplitude deviation (MAD) is a good parameter to distinguish the intensity of physical activity. Here, the aims of the present study were twofold: a) to develop a new EE estimation equation using raw accelerometer data and heart rate, and b) to compare the oxygen consumption measured with the new equation developed and the most commonly used prediction equations in the literature in normal weight and overweight adults.
*Equipment and methods.* — Twenty healthy adults (10 males and 10 females) wore a wearable device on the chest that integrates triaxial accelerometry and ECG signals. The test protocol consisted in 12 individualized intensities, 6 walking and 6 running speeds equally distributed. The correlation between MAD and measured oxygen consumption was investigated. Then, a new energy expenditure estimation equation was developed and compared with five formulas from the literature.
*Results.* — Our results noted that MAD had a very high correlation ($r = 0.937$) with indirect calorimetry. The new equation developed had one of the two lowest mean absolute errors for both walking and running. Therefore, our equation appears to be suitable for both walking and running, for normal weight and overweight people. However, future studies should validate our new EE estimation equation with a wide range of population and field-based conditions.
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**Résumé**

*Objectifs.* — Une détermination précise de la dépense énergétique (EE) par accélérométrie est importante pour l'efficacité des programmes d'AP. L'écart d'amplitude moyen (MAD) est un bon paramètre pour distinguer l'intensité de l'activité physique. Ici, les objectifs de la présente étude étaient doubles: a) développer une nouvelle équation d'estimation de l'EE utilisant les données brutes de l'accéléromètre et la fréquence cardiaque, et b) comparer la consommation d'oxygène mesurée avec la nouvelle équation développée et les équations de prédiction les plus utilisées la littérature chez les adultes de poids normal et en surpoids.

*Matériel et méthodes.* — Vingt adultes en bonne santé (10 hommes et 10 femmes) portaient un appareil portable sur la poitrine qui intègre des signaux d'accélérométrie triaxiale et d'ECG. Le protocole de test consistait en 12 intensités individualisées, 6 vitesses de marche et 6 vitesses de course également réparties. La corrélation entre la MAD et la consommation d'oxygène mesurée a été étudiée. Ensuite, une nouvelle équation d'estimation de la dépense énergétique a été développée et comparée à cinq formules de la littérature.

*Résultats.* — Nos résultats ont noté que MAD avait une très forte corrélation ($r = 0,937$) avec la calorimétrie indirecte. La nouvelle équation développée avait l'une des deux erreurs absolues moyennes les plus faibles pour la marche et la course. Par conséquent, notre équation semble convenir à la fois à la marche et à la course, aux personnes de poids normal et en surpoids. Cependant, les études futures devraient valider notre nouvelle équation d'estimation de l'EE avec un large éventail de conditions de population et de terrain.

## 1. Introduction

The 2002 World Health Report indicates that sedentary lifestyle is one of the 10 leading causes of death and disability [1]. Physical inactivity increases the risk of developing cardiovascular diseases [2] and type 2 diabetes [3]. Moreover, the lack of physical activity (PA) has been associated with poor levels of quality of live [4] and with some types of cancer [5]. Thus, several methods have been proposed to assess PA such as doubly labelled water [6], indirect calorimetry [7], self-report questionnaires [8], heart rate (HR) monitors [9] and motion sensors [10,11]. Accurate determination of energy expenditure (EE) is relevant in the effectiveness of the PA programs, and its measurement provides information about the person's overall activity pattern [12]. Stepwise protocols to increase PA are included, for instance, in the rehabilitation treatment of cardiac diseases [13].

In the literature, there are some algorithms and equations to estimate EE. On the one hand, some of them use walking or running speed, anthropometric data and heart rate [14—16]. On the other hand, there has been a growing interest in the development of wearable devices with accelerometers and heart rate sensors incorporated, having the main purpose the assessment of PA levels through EE estimation. Although HR and accelerometry have their own strengths and weakness in the field of PA assessment, some authors state that the combination of HR and accelerometry improves the accuracy of the EE estimation [17]. Indeed, the integration of accelerometry and HR sensors in the same wearable device is advisable [18].

In terms of accelerometry, a considerably controversy exists about which parameter is more valid and accurate to use in PA estimation equations. Mostly of prediction equations of EE report their outcomes in counts, which is an aggregate measure of amount and intensity of activity over a specific time period [19]. However, Crouter et al.

[11] compared 14 published regression equations from the accelerometer counts with indirect calorimetry in different activities and intensities, and concluded that no single regression equation works well across the wide range of activities evaluated. Besides, Sasaki et al. [20] and Chowdhury et al. [21] assessed the performance of different PA monitors and the results, standard error of estimate and correlation with the indirect calorimetry values were contrasting in all cases. The reason might be that counts are generated by proprietary algorithms with restricted information [19,22]. Manufacturers protect their algorithms, and researchers cannot perform repeatable procedures with the different wearable devices we can find in the market. Hence, Vähä-Ypyä et al. [19] calculated and compared the performance of thirteen time and frequency domain traits from the measured raw data of accelerometry. They concluded that the mean amplitude deviation (MAD) provided the best performance. MAD describes the typical distance of data points about the mean and is defined as follows (1):

$$MAD = \frac{1}{n}\sum_{i=1}^{n}\left|r_i - \overline{r}\right| \qquad (1)$$

Our research group was able to prove that MAD is a good parameter to distinguish the intensity of physical activity, classifying correctly 93% of the cases [23]. Now, the aims of the present study were twofold: (a) to develop a new EE estimation equation using raw data accelerometer and heart rate and; (b) to compare the oxygen consumption measured with the new equation developed and the most commonly used prediction equations in the literature that use walking or running speed as input to predict EE in normal weight and overweight adults.

**Table 1** Physical characteristics of the study participants ($n = 20$). Values expressed as the mean $\pm$ SD.

|  | Age (y) | Weight (kg) | Height (m) | BMI |
|---|---|---|---|---|
| Low BMI ($n = 10$) | $30 \pm 9.2$ | $59.17 \pm 8.71$ | $1.71 \pm 0.13$ | $20.17 \pm 0.81$ |
| High BMI ($n = 10$) | $40.2 \pm 9.3$ | $78.86 \pm 13.63$ | $1.67 \pm 0.14$ | $28.17 \pm 1.17$ |

## 2. Materials and methods

### 2.1. Participants

Twenty healthy participants (10 males and 10 females) were recruited for this investigation. The participants' physical characteristics are presented in Table 1. Two groups of ten people were established depending on their body mass index (BMI). Low BMI group was ranged between 19 and 22, and High BMI group 26 to 29. All participants self-reported to be free from any cardiac disease or injury that could limit their ability to complete the test. Participants refrained from strenuous exercise and caffeine for a minimum of 24 hours before the testing session. The study protocol adhered to the tenets of the Declaration of Helsinki and received Institutional Ethics Committee approval. All participants gave their informed, written consent.

### 2.2. Procedures

The test protocol consisted in 12 individualized intensities, 6 walking and 6 running speeds. They were established during the warm-up according to their individual fitness. Regarding walking and running modalities, participants had to report three speeds. For walking modality, one was a comfortable walking speed that they were used to go for a walk, and the other was that speed they could walk and jog. From this range, we got 6 walking speeds equally distributed. For the running modality, the maximum speed from walking modality was the same for the lowest running speed (a light jogging). The maximum running speed corresponded to that speed they could maintain at least 4 minutes. From this range, it was established 6 running speeds equally distributed. Having their individual speeds, all participants performed their 12 speeds in a randomized order. Each speed lasted 3 minutes and between them there was a rest time for 1 minute after walking speeds and 2 minutes after running speeds. Three minutes was enough time to measure stable oxygen consumption at a constant speed [24]. From this time, to ensure steady-state EE, the last two minutes for each speed were taken into account for the energy consumption measurement and data analysis. Before warm up period it was also measured the resting energy expenditure and resting HR (HRrest) from 5 minutes in a sitting position.

The tests were performed on a calibrated treadmill (HP Cosmos, Mercury, Germany) with a 1% treadmill grade [25]. All participants performed the tests in the early morning, with the same conditions of temperature and humidity.

### 2.3. Accelerometry and heart rate wearable device

The nECG MINDER (Nuubo, Spain) is a small ($77 \times 50 \times 19$ mm) and lightweight (56.1 g) placed on the chest that integrates triaxial accelerometry and ECG signals. The electrocardiographic signal is captured by 2 sensor electrodes of the textile and registered by the attachable wireless device. The textile electrodes must be wet with gel, placed on healthy skin and never on skin with wounds. All data captured is saved on an internal micro-SD memory card, with a sampling rate of 250 Hz. A miniUSB to USB cable was used to transfer data from the micro-SD card to the PC.

### 2.4. Oxygen consumption measurement

Energy expenditure was measured by indirect calorimetry utilizing open circuit spirometry of a portable metabolic system (COSMED K4b$^2$, Italy). The participants wore this system continuously during the protocol. It has been shown to be both valid and reliable [26,27]. This system consists of a facemask connected to the storage and telemetry unit through a sampling line. Every day before starting the tests, the system was warmed up for 30 minutes and calibrated according to manufacturer's instructions. Relative humidity, ambient temperature and participants' body mass were entered into the portable unit prior to the test.

### 2.5. Energy expenditure estimation equations

Numerous formulas have been used in the literature for the estimation of energy expenditure in walking and running. We selected the following equations because researchers and physiologists commonly used them in their research and scientific publications. These formulas come next:

EQ1 — Glass & Dwyer [14]:

Walk: $VO_2$ (ml/kg/min) $= 0.1 \times S + 1.8 \times S \times$ fractional grade $+ 3.5$

Run: $VO_2$ (ml/kg/min) $= 0.2 \times S + 0.9 \times S \times$ fractional grade $+ 3.5$

[S: speed in m/min; fractional grade is in decimal form, 5% grade is 0.05].

EQ2 — van der Walt & Wyndham [15]:

Walk: $VO_2$ (l/min): $0.00599 \times M + 0.000366 \times M \times V^2$

Run: $VO_2$ (l/min): $-0.419 + 0.03257 \times M + 0.000117 \times M \times V^2$

[M: body mass (kg), V: velocity (km/h)]

EQ3 — Léger & Mercier [28]:

$VO_2$ (ml/kg/min) $= 2.209 + 3.1633 \times S$

[S: running speed in km/h]

EQ4 — Pettitt et al. [29]:

METs $= 6 \times$ HRindex $- 5$

[HRindex = HRabsolute/HRrest; HR: Heart Rate; HRrest: resting heart rate; 1 MET = 3.5 ml/kg/min]

EQ5 — Keytel et al. [30]:

EE (kJ/min) = gender $\times (-55.0969 + 0.6309 \times$ heart rate $+ 0.1988 \times$ weight $+ 0.2017 \times$ age) $+ (1 - $ gender) $\times$

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**Table 2** Pearson's product-moment correlations between $VO_2$ and speed and MAD.

| | Speed (km/h) | | | | | MAD | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | cor | 95% CI | n | t (df) | P-value | cor | 95% CI | n | t (df) | P-value |
| $VO_2$ (ml/kg/min) | 0.934 | [0.916, 0.949] | 238 | 40.328 (236) | < 0.001 | 0.937 | [0.919, 0.951] | 238 | 41.229 (236) | < 0.001 |

$(-20.4022 + 0.4472 \times heart\ rate - 0.1263 \times weight + 0.074 \times age)$

[1 l $O_2$/min = 20 kJ/min; Male = 1, Female = 0]

## 2.6. Statistical analysis

Indirect calorimetry was used as the gold standard and reference values. First, were conducted to identify if a relationship existed between walking and running speed and MAD with $VO_2$ measured through indirect calorimetry. Second, Analysis of Variance (Anova) was calculated to determine a possible effect of different variables, additionally to MAD, in EE. Third, we developed the coefficients of the regression model with the selected variables previously from Anova. Finally, through Leave-one-out cross-validation, we obtained the absolute errors of our new formula and the EE estimation equations of the literature, and compared with the measured results of the gold standard. We decided to take into account absolute errors because negative errors could compensate the positives. Therefore, absolute error avoids this issue. Mean absolute error is better to compare the reliability of the equations. Statistical significance was set at the 0.05 level. The programming language R version 2.7.0 (23) was used to develop the new estimation equation and to perform the statistical analyses.

## 3. Results

In Table 2 is shown the Pearson's product-moment correlations between speed and MAD with oxygen consumption. Although both parameters had almost the same correlation, MAD had the highest, $r = 0.937$ (Fig. 1).

Table 3 showed the results of Anova. The variables with significant effect in EE were MAD, HRindex, age, gender and condition (walking or running). BMI had not influence. Hence, the coefficients of our model are presented in Table 4.

The new EE estimation equation (2) developed in this work is the following:

$VO2 = 8.62121 + 29.10141 \times MAD - 0.08096 \times Age +$

$2.84826 \times HRindex - 1.81686 \times Gender$ (2)

where $VO_2$ is expressed in ml/kg/min; gender = 0 for males and 1 for females.

Measured values of EE for each speed were compared with values of the new equation developed and with different EE estimation equations published in the literature. In Fig. 2 can be seen the difference between the new developed equations and measured values of EE for both walking and running. As expected, in general, the differences
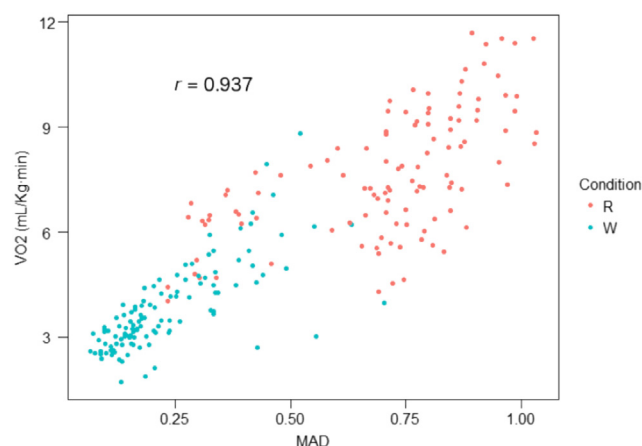


**Figure 1** Correlation between $VO_2$ and MAD. R: running; W: walking; MAD: mean amplitude deviation.

in walking were lower than in running. Otherwise, the mean absolute errors for the total duration of each speed (2 minutes) are presented in Table 5 and Fig. 3. For running, the new equation developed and EQ1 [31] had the lowest mean absolute errors comparing with measured values. For walking, our new equation and EQ3 [28] had the lowest mean absolute errors.

## 4. Discussion

The aims of this study were to develop a new equation using raw accelerometer data and heart rate, and to compare this formula with other EE estimation equations from the literature that researchers and physiologists commonly used in their research. On the basis of the good performance of MAD to classify PA intensity, previously investigated by our research group [23], in the present study we found that MAD had a very good correlation with $VO_2$ ($r = 0.937$). This is a higher correlation than Eston et al. [32] found between accelerometer output during treadmill walking and oxygen uptake ($r = 0.88$). In our study, walking or running speed had also a very good correlation ($r = 0.934$), however in some situations is not possible to obtain the activity speed through global positioning system (GPS) receivers, for example, indoors, or fitness trackers without GPS. Moreover, when exercise is performed outdoors and GPS is an option to determine the activity speed, there are some disadvantages to take into account. If we seek a high accuracy of speed determination, relatively straight courses are advisable, by contrast, errors increase on circular paths [33]. This situation could be solved with a wearable device with an accelerometer and heart rate sensors included, estimating

**Table 3**   Anova results.

|  | Sum Sq | Df | F value | Pr (> F) | P value |
|---|---|---|---|---|---|
| MAD | 2904.52 | 1 | 250.8245 | 2.2e-16 | **** |
| HRindex | 93.26 | 1 | 8.0540 | 0.0049443 | *** |
| Age | 133.62 | 1 | 11.5391 | 0.0008023 | **** |
| BMI | 1.88 | 1 | 0.1619 | 0.6877545 | * |
| Gender | 233.90 | 1 | 20.1992 | 1.104e-05 | **** |
| Condition | 66.61 | 1 | 5.7525 | 0.0172600 | ** |
| Residuals | 2674.95 | 231 |  |  | * |

* $P < 0.10$.
** $P < 0.05$.
*** $P < 0.01$.
**** $P < 0.001$.

**Table 4**   Regression coefficients of the new EE estimation equation developed.

|  | Estimate | Std. Error | t value | Pr (>|t|) | P value |
|---|---|---|---|---|---|
| (Intercept) | 8.62121 | 1.31048 | 6.579 | 3.10e-10 | ** |
| MAD | 29.10141 | 1.22548 | 23.747 | 2e-16 | ** |
| Age | −0.08095 | 0.02423 | −3.341 | 0.000973 | ** |
| HRindex | 2.84826 | 0.97703 | 2.915 | 0.003901 | * |
| Gender | −1.81686 | 0.45665 | −3.979 | 9.26e-05 | ** |

* $P < 0.01$.
** $P < 0.001$.
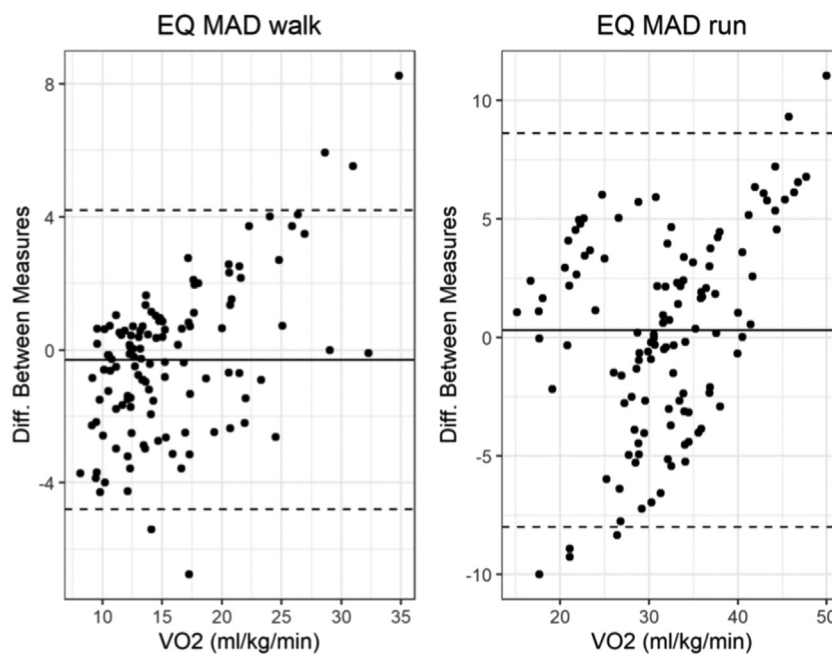


**Figure 2**   Bland — Altman plot comparison between the new equation developed and measured values of EE. Left: NEW EQ walk VS measured values of EE; Right: NEW EQ run VS measured values of EE.

EE from these inputs as we proposed in this study. Besides, others researchers [34] presented two separate artificial neural networks, one to estimate EE and other to estimate activity type. Here we present MAD as the unique algorithm to classify PA type and estimate EE, being a significant advantage in practical application.

To the best of our knowledge, this is the first study that comprises a non-proprietary algorithm to estimate EE compared with indirect calorimetry. Regarding the accuracy of the devices tested in different studies, contrasting results were found when assessing the same activities [11]. A recent study [21] noted that some devices underestimated

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**Table 5** Absolute errors of EE estimation of the new equation and previously published in literature comparing with measured EE, for running and walking.

|  | Error | n | Mean | SD | Min | Max |
|---|---|---|---|---|---|---|
| Running | EQ1 | 118 | 3.12 | 2.42 | 0.05 | 11.69 |
|  | EQ2 | 118 | 7.05 | 4.94 | 0.19 | 21.50 |
|  | EQ3 | 118 | 5.50 | 2.90 | 0.02 | 15.41 |
|  | EQ4 | 118 | 9.42 | 5.86 | 0.23 | 28.91 |
|  | EQ5 | 118 | 7.31 | 6.23 | 0.03 | 21.88 |
|  | NEW | 118 | 4.02 | 2.86 | 0.09 | 11.95 |
| Walking | EQ1 | 120 | 3.53 | 3.03 | 0.04 | 16.57 |
|  | EQ2 | 120 | 9.06 | 5.06 | 2.00 | 27.25 |
|  | EQ3 | 120 | 1.93 | 1.53 | 0.01 | 8.89 |
|  | EQ4 | 120 | 4.17 | 3.22 | 0.07 | 19.10 |
|  | EQ5 | 120 | 7.63 | 4.85 | 0.17 | 23.06 |
|  | NEW | 120 | 2.08 | 1.82 | 0.02 | 8.66 |

Values are expressed in ml/kg/min.
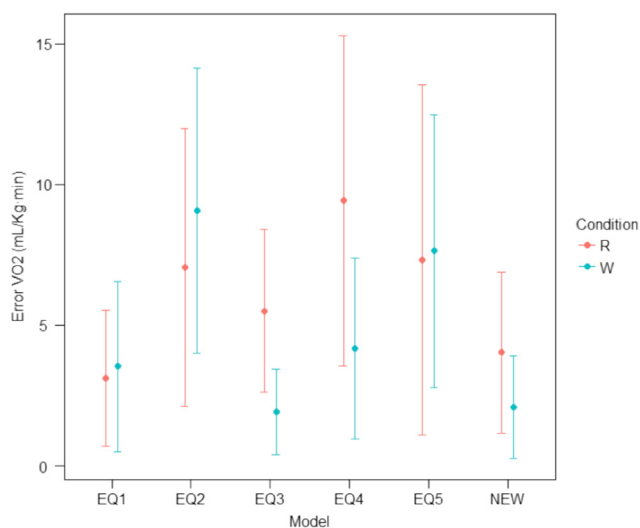


**Figure 3** Absolute errors of EE estimation of the new equation and previously published in literature comparing with measured EE. R: running; W: walking.

free-living EE in around 400 kcal/day. In the other hand, in walking and running, some of the 6 devices tested overestimated and others underestimated 2 to 3 kcal·min$^{-1}$ when compared with the measured EE. Different activity monitors can give significant differences in count values, even when same human movement is been evaluating. This fact leads to be cautious when lifestyle decisions around energy balance, such as nutrition or PA programs, have to be taken.

Our findings partially agree with those of Hall et al. [35], who reported that EQ1, from Glass & Dwyer [14], appeared to be the most suitable formula for walking and running. Our results showed that, for running, EQ1 and our new equation had the lowest mean absolute errors compared with measured values of oxygen consumption, giving errors of 3.12 ± 2.42 and 4.02 ± 2.86 ml/kg/min respectively for the total duration of each speed evaluated. With respect to walking condition, EQ3, from Léger and Mercier [28], and our new equation had the lowest mean absolute errors, 1.93 ± 1.53 and 2.08 ± 1.82 ml/kg/min respectively.

Therefore, our new EE estimation equation appears to be suitable for both walking and running, for normal weight and overweight people. However, future studies should validate our new EE estimation equation with a wide range of population (e.g. children or adults with different BMI) and out of laboratory-based conditions.

## Disclosure of interest

The authors declare that they have no competing interest.

## Acknowledgments

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