Evaluation of heart rate as a method for assessing moderate intensity physical activity

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ABSTRACT

STRATH, S. J, A. M. SWARTZ, D. R. BASSETT, JR., W. L. O'BRIEN, G. A. KING, and B. E. AINSWORTH. Evaluation of heart rate as a method for assessing moderate intensity physical activity. *Med. Sci. Sports Exerc.*, Vol. 32, No. 9, Suppl., pp. S465–S470, 2000. To further develop our understanding of the relationship between habitual physical activity and health, research studies require a method of assessment that is objective, accurate, and noninvasive. Heart rate (HR) monitoring represents a promising tool for measurement because it is a physiological parameter that correlates well with energy expenditure (EE). However, one of the limitations of HR monitoring is that training state and individual HR characteristics can affect the HR–$\dot{V}O_2$ relationship. **Purpose:** The primary purpose of this study was to examine the relationship between HR (beats·min^{-1}) and $\dot{V}O_2$ (mL·kg^{-1}·$^{-1}$min^{-1}) during field- and laboratory-based moderate-intensity activities. In addition, we examined the validity of estimating EE from HR after adjusting for age and fitness. This was done by expressing the data as a percent of heart rate reserve (%HRR) and percent of $\dot{V}O_2$ reserve (%$\dot{V}O_{2R}$). **Methods:** Sixty-one adults (18–74 yr) performed physical tasks in both a laboratory and field setting. HR and $\dot{V}O_2$ were measured continuously during the 15-min tasks. Mean values over min 5–15 were used to perform linear regression analysis on HR versus $\dot{V}O_2$. HR data were then used to predict EE (METs), using age-predicted HR_{max} and estimated $\dot{V}O_{2max}$. **Results:** The correlation between HR and $\dot{V}O_2$ was r = 0.68, with HR accounting for 47% of the variability in$\dot{V}O_2$. After adjusting for age and fitness level, HR was an accurate predictor of EE (r = 0.87, SEE = 0.76 METs). **Conclusion:** This method of analyzing HR data could allow researchers to more accurately quantify physical activity in free-living individuals. **Key Words:** KARVONEN FORMULA, ENERGY EXPENDITURE, OXYGEN UPTAKE, EXERCISE

Over the last four decades, there has been substantial evidence to support the importance of habitual physical activity (PA) in maintaining good health and avoiding chronic disease (17). To further develop our understanding of the association between habitual PA and health, and to define an optimal quantity of PA needed to produce improvements in health, accurate methods of PA assessment are needed. At present, researchers encounter difficulties in measuring habitual PA levels noninvasively and accurately (10,16). To further explore the relationship between PA and health, a method that would address these issues is required.

Heart rate (HR) has been commonly employed as an objective method of assessing PA (6,20,23,26). The use of HR as a measure of PA is promising because it is a physiological parameter known to have a strong positive association with energy expenditure (EE) during large muscle dynamic exercise (7). HR has been shown to be valid compared with ECG monitoring in both the laboratory (12,14,23) and field settings (23). Reproducibility within subjects has also been shown to be quite high (25). HR recording is a method that is relatively low cost, noninvasive, and able to give information on the pattern of physical activity. In addition, technological advancements now enable HR recorders to store information over a period of days or weeks, thus providing data on various components of PA, including frequency, intensity and duration.

Various techniques have been presented in the literature for using HR data as an estimate of EE. Average pulse rate has been used as a predictor of daily EE (7,18). A second method uses net HR (activity HR –resting HR), which has been shown to be a simple and relatively accurate method for assessing EE in the field (26). A third approach was single and multiple individual HR–$\dot{V}O_2$ calibration curves performed in the laboratory, which offers the most accurate way to predict EE (1,3,15,18). This approach accounts for differences in $\dot{V}O_{2max}$ and HR_{max} that exist between individuals. However, the latter technique cannot be employed in large-scale epidemiological studies due to limitations in both time and expense.

The primary purpose of this study was to examine the

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laboratory based moderate intensity activities. However, factors such as the individual's age and fitness level can affect the HR–$\dot{V}O_2$ relationship. Thus, a secondary purpose was to examine the validity of using HR data to predict EE, after adjustment for age and fitness. This was accomplished by expressing the data as a percent of heart rate reserve (%HRR) and percent of $\dot{V}O_2$ reserve (%$\dot{V}O_{2R}$). The latter variables, %HRR and %$\dot{V}O_{2R}$, have been shown to be tightly coupled and numerically similar over the entire range of exercise intensities (21,22). This method allowed us to predict EE in METs (1 MET = average rate of EE at rest, or 3.5 mL·kg^{-1}·$^{-1}$min^{-1}), based on the activity HR and well-established physiological relationships.

METHODS

Eighty-one participants (19–74 yr) volunteered to take part in this study. Twenty participants were excluded due to HR data not being collected. Therefore, 61 people (14% African American, 3% Asian, 1% Hispanic, and 82% Caucasian), including 31 men (age 41 ± 13 yr, BMI 26.2 ± 5.7 kg·m^2, mean ± SD) and 30 women (age 40 ± 12 yr, BMI 27.1 ± 6.2 kg·m^2, mean ± SD), were included in this study. All participants were recruited from within the university and surrounding community through public postings and word of mouth. Each participant read and signed an informed consent approved by the University of Tennessee Institutional Review Board. Along with the informed consent, the participants completed a physical activity readiness questionnaire (PAR-Q).

Before testing, each subject's height and weight (one layer of clothes, no shoes) were measured via a stadiometer and a standard physician's scale respectively. Body density and percentage of body fat were estimated from skinfolds using the three site equations of Pollock et al. (chest, abdomen and thigh for men; tricep, suprailiac, and thigh for women) by means of Lange Calipers (Cambridge, MD) (19).

Procedures. Each participant performed from one to seven of the following activities:

Activities performed at the participants' homes and at local golf and tennis clubs:

Inside. Vacuuming, sweeping and mopping, laundry, ironing, washing dishes, cooking, light cleaning, and grocery shopping with a cart, feeding and grooming animals, and caring for small children.

Outside. Mowing the lawn (manual and power mowers), raking, trimming, and gardening, playing with children in the yard, and playing with animals in the yard, doubles tennis, golf-carrying clubs, golf-pulling clubs, and softball.

Activities performed in the University of Tennessee's Applied Physiology Laboratory and surrounding grounds:

Inside. Walking at 67 m·min^{-1} while carrying items of 6.8 kg, walking at 93.8 m·min^{-1} while carrying items of 6.8 kg; loading and unloading boxes of 6.8 kg; stretching and light calisthenics.

Outside. Slow walk (average 78 m·min^{-1}) and fast walk

Activities were performed for 15 min at the participants' own self-selected pace. Before each activity, and between activities, the participant was asked to sit quietly for 5 min.

Indirect calorimetry. Each participant wore the Cosmed K4b^2 (Cosmed S.r.I, Rome, Italy), a portable indirect calorimetry system, while performing every activity and throughout the rest periods. The Cosmed K4b^2 unit was mounted on the participant via a chest harness. A flexible face mask (Hans-Rudolph, Kansas City, MO), with disposable gel seal, covered the participant's mouth and nose and was attached to a flowmeter. The face mask and adjoining flowmeter were secured to the participant via a head strap. The flowmeter is a bi-directional digital turbine and uses an opto-electric reader. The Cosmed K4b^2 oxygen analyzer and the carbon dioxide analyzer were calibrated immediately before each test session according to manufacturer's guidelines. After the calibration process was completed, subject characteristics (age, gender, height and weight) were entered into the Cosmed K4b^2.

Heart rate monitoring. The Cosmed K4b^2 also recorded HR throughout each activity, via a Polar HR transmitter (Polar Electro, Tampere, Finland). As previously cited, the use of HR recording has been shown to be valid in both laboratory (12,14,23) and field settings (23). The Cosmed K4b^2 uses a Polar HR "detection board" (PCBA receiver 380193) to receive HR data from the Polar HR transmitter. This is the same technology as that found in Polar heart watches, which have previously been shown to be valid (13). We decided to further assess its accuracy in a validation study among a subgroup of eight volunteers from this study. In this validation study, HR was measured during the final minute of successive 3-min stages, which included seated rest on a Monark 818E cycle ergometer (Varberg, Sweden) and pedaling at power outputs of 50, 100, 150, and 200 W. The correlation between HR, from the Cosmed K4b^2, and an ECG tracing (Burdick EK10, Milton WI), using the number of complete cardiac cycles in a 60's interval (Lead II), was r = 1.00, SEE = 0.65 beats·min^{-1}.

Nonexercise $\dot{V}O_{2max}$ and HR_{max} prediction. A nonexercise prediction equation estimate of $\dot{V}O_{2max}$ and age-predicted HR_{max} was employed. $\dot{V}O_{2max}$ was predicted for each participant using the equation of Jackson et al. (9), which incorporated physical activity level, age in years, percent body fat, and gender. Physical activity status was evaluated using a 0–7 scale, which was developed by NASA's Johnson Space Center and used by Jackson et al. (9,21). Body density, and subsequently percent body fat, was estimated from skin-fold measures as described previously. The Jackson et al. (9) equation follows:

$$\dot{V}O_{2max}\ (\text{ml·kg·}^{-1}\text{min}^{-1}) = 50.513 + 1.589\ (\text{PA}[0–7]) - 0.289(\text{yrs}) - 0.552(\%\text{fat}) + 5.863(\text{F} = 0, \text{M} = 1).$$

%$\dot{V}O_{2R}$ was then calculated using predicted $\dot{V}O_{2max}$, and the measured resting and activity $\dot{V}O_2$ values. The use of $\dot{V}O_{2R}$was employed rather than %$\dot{V}O_{2max}$, as it has recently

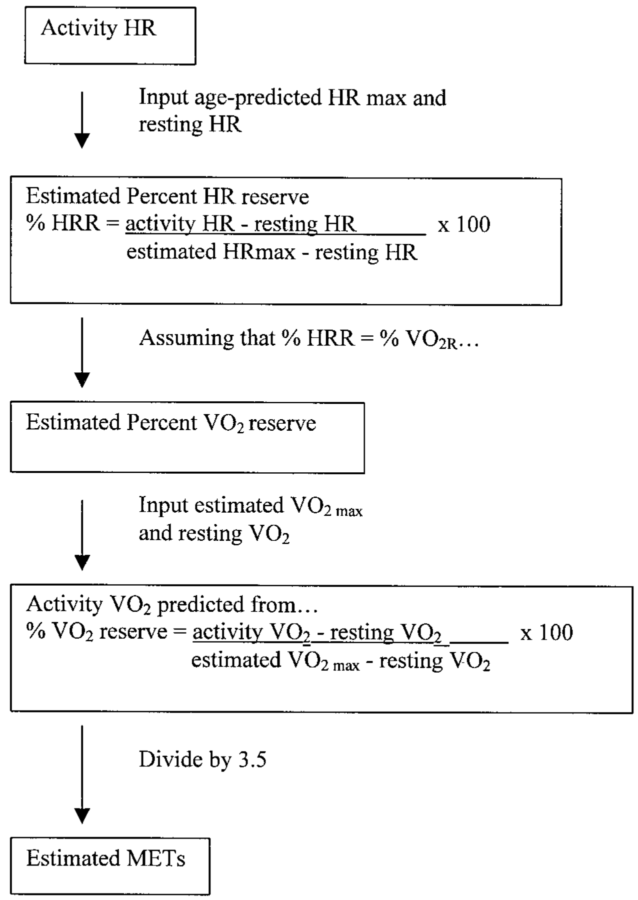

Figure 1—Flow diagram demonstrating the use of activity HR to calculate EE (METs) via age-predicted %HRR and estimated %$\dot{V}O_{2R}$.

Calculations. The oxygen uptake and HR data from the Cosmed K4b^2 were stored in memory and directly downloaded to a Windows-based laptop PC after the test was completed. EE in METs was computed from the participants' activity HR (Fig. 1). Recorded HR values were transformed into %HRR values by utilizing the formula:

$$\%HRR = [(\text{activity HR} - \text{resting HR})/(\text{est. HR}_{max} - \text{resting HR})]*100\%$$

where HR_{max} was assumed to equal 220 minus age (yr) (11). Taking into consideration that %HRR is approximately equal to the %$\dot{V}O_{2R}$, as shown by Swain et al. (21,22), the relative intensity of the exercise bout was determined. %$\dot{V}O_{2R}$ for each activity was transformed to an absolute oxygen consumption ($\dot{V}O_2$ mL·kg^{-1}·$^{-1}$min^{-1}) using the formula:

$$\%\dot{V}O_{2R} = [(\text{activity } \dot{V}O_2 - \text{resting } \dot{V}O_2)/(\text{est. } \dot{V}O_{2max} - \text{resting } \dot{V}O_2)]*100\%$$

where $\dot{V}O_{2max}$ was obtained from the nonexercise prediction equation of Jackson et al. (9). $\dot{V}O_2$ (mL·kg^{-1}·$^{-1}$min^{-1}) was converted to METs by dividing by 3.5.

Statistical analysis. Minute-by-minute values were obtained for HR and $\dot{V}O_2$. For each subject, the mean HR (beats·min^{-1}) and mean $\dot{V}O_2$ (mL·kg^{-1}·min^{-1}) was com-

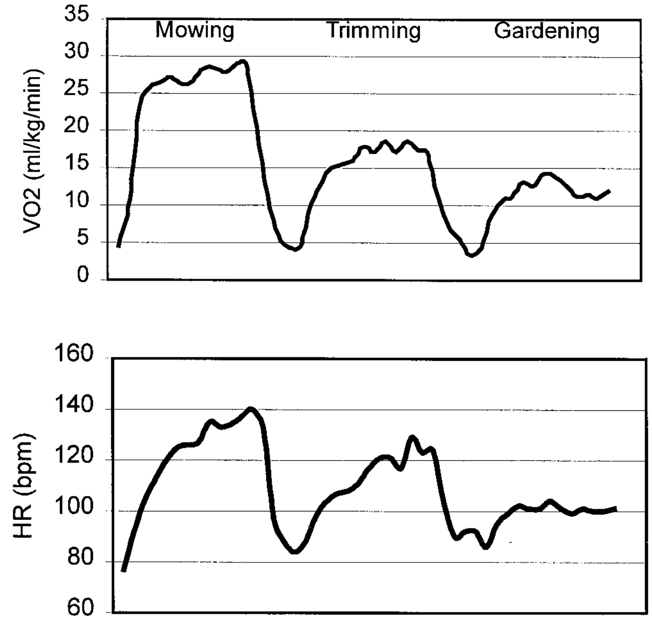

Figure 2—Minute-by-minute tracking of $\dot{V}O_2$(mL·kg^{-1}·min^{-1}) and HR (beats·min^{-1}) for the activities of lawn mowing (manual push mower), trimming (electric), and gardening (pulling weeds, planting flowers).

puted from minutes 5–15 for each activity. Statistical analyses were performed within SPSS 9.0 for Windows (Chicago, IL). The mean values for the subjects were then pooled and a linear regression analysis was performed to demonstrate the relationship between EE and HR. In addition, correlational analysis was used to determine the validity of estimating EE from activity HR after adjustment for individual age and fitness level. A Bland-Altman plot was constructed to show the relationship of the error score (measured EE –estimated EE) across a wide range of exercise intensities.

RESULTS

The ability of HR to track $\dot{V}O_2$ during activity is shown in the minute-by-minute graph of HR (beats·min^{-1}) and $\dot{V}O_2$ (mL·kg^{-1}·$^{-1}$min^{-1}) for an activity period that included: lawn mowing (manual push mower), trimming (electric), and gardening (pulling weeds, planting flowers) (Fig. 2).

Figure 3 shows the relationship between HR (beats·min^{-1}) and oxygen uptake (mL·kg^{-1}·$^{-1}$min^{-1}) with a correlation of $r = 0.68$. Heart rate accounted for 47% of the variability in oxygen uptake, SEE = 18.23 mL·kg^{-1}·$^{-1}$min^{-1}.

Figure 4 shows the relationship between measured EE and estimated EE (using HR data and adjusting for age and fitness) with a correlation of $r = 0.87$. Estimated EE accounted for 78% of the variability in measured EE, SEE = 0.76 METs.

Figure 5 highlights the relationship of the error score (measured EE –estimated EE) across a wide range of exercise intensities, mean error = 0.04 METs, 95% confidence interval (CI) = (−1.48, 1.56) METs.

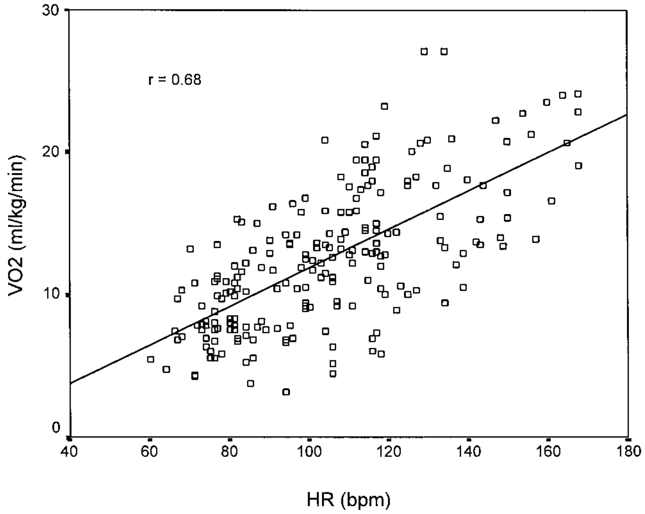

Figure 3—Relationship between HR (beats·min^{-1}) and $\dot{V}O_2$ (mL·kg^{-1}·min^{-1}).

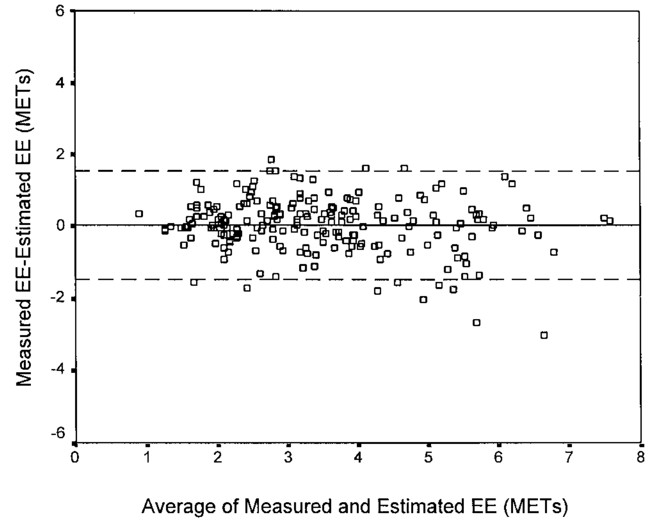

Figure 5—Bland-Altman plot showing the relationship of the error score (measured EE –estimated EE) across a wide range of exercise intensities.

DISCUSSION

This study found that HR (beats·min^{-1}) is moderately correlated to $\dot{V}O_2$ (mL·kg^{-1}·$^{-1}$min^{-1}) during field and laboratory activities (r = 0.68). Rodahl et al. (20) looked at the relationship between simultaneously recorded HR and $\dot{V}O_2$ in Nordic ocean fishermen. Oxygen uptake was measured by the Douglas bag method during specific activities. The measured $\dot{V}O_2$ values were compared with predicted $\dot{V}O_2$ values estimated from the HR–$\dot{V}O_2$ relationship determined in the laboratory. The results showed that the predicted $\dot{V}O_2$ values deviated from the measured values by no more than ± 15% (20).

Individual variation in gender, age, and training status have been shown to affect the HR–$\dot{V}O_2$ relationship (5). It has long been known that trained persons have a lower HR at a given $\dot{V}O_2$ (4). Thus, if one correlates HR versus $\dot{V}O_2$, the correlation can be low because it does not take into account that a more highly fit individual has a lower HR at any given $\dot{V}O_2$. This factor causes difficulty for the estimation of EE from raw HR.

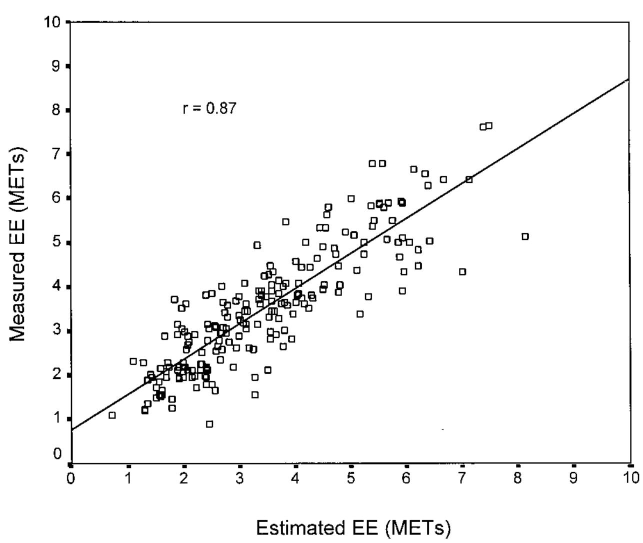

Figure 4—Relationship between measured METs and estimated MET

The relationship between markers of relative intensity (%HRR and %$\dot{V}O_{2R}$) is much tighter than the relationship between HR and $\dot{V}O_2$ (21,22). Therefore, we applied the well-established equations for age-predicted HR_{max} (11) and nonexercise estimates of $\dot{V}O_{2max}$ (9) to allow the relative intensity of the activity to be expressed. A limitation of the present study was that we did not directly measure maximal exercise values. However, this might be impractical and/or unfeasible in larger studies, particularly those studies where elderly participants are involved. Despite this limitation, our findings were in agreement with those of Swain et al. (21,22), who demonstrated a strong numerically similar relationship between %HRR and %$\dot{V}O_{2R}$ in the laboratory. Had we actually measured HR_{max} and $\dot{V}O_{2max}$, it would have most likely improved the estimate of EE.

An important advantage of using HR over motion sensors is that HR monitoring provides an index of both the relative (%$\dot{V}O_{2R}$), as well as the absolute intensity (METs) of the physical activity performed. The importance of relative intensity can be seen when classifying different individuals on the basis of exercise intensity. The recommendation of the Centers for Disease Control and Prevention and the American College of Sports Medicine states that every U.S. adult should accumulate 30 min or more of moderate intensity physical activity on most, preferably all, days of the week (17). Moderate intensity refers to an intensity level of 3–6 METs. However, the use of absolute cut points, such as 3 and 6 METs, holds limited validity when considering populations of different ages and different fitness levels. Six METs could be perceived as "light" for a young athlete, but "hard" for an 80-yr old person. Figure 4 highlights this fact. The activities undertaken in this study were thought to represent moderate intensity physical activity; however, there were a number of older subjects who were above this level of intensity and approached 80–100% of their esti-

To account for this problem, the Surgeon General's report on *Physical Activity and Health* suggests the use of age-adjusted absolute MET cut points (24). However, an alternative approach suggested in the report is the use of five relative intensity categories: very light (<25%), light (25–44%), moderate (45–59%), hard (60–84%), and very hard (≥85%). In fact, it may be preferable to limit the number of categories to lower the possibility of misclassification, and use relative intensity cut points of less than 30% (light), 30 to 60% (moderate) and greater than 60% (hard).

Figure 2 shows the time course of changes in $\dot{V}O_2$ and HR for the activities of mowing, trimming, and gardening. From this figure it can be seen that HR takes 2- to 3-min to increase to a level representative of the activity being performed, as does $\dot{V}O_2$, the gold standard for EE measurement. Likewise, at the termination of activity, both HR and $\dot{V}O_2$ take a few minutes to decrease to resting levels. This is different from the instantaneous response known to occur with motion sensors. With regard to motion sensors, other papers in this series have reported on their accuracy in estimating EE (2,8,27). Such studies have found lower correlation coefficients ($r = 0.4–0.6$) between EE and accelerometers during "lifestyle activities," than the one shown in this paper between EE and the HR method ($r = 0.87$). In addition, the variation of error involved in the HR method is less than those seen with motion sensors during "lifestyle activities" (2). The 95% CI of the error score was (−1.48, 1.56) METs, as compared with those seen with motion sensors, ranging from approximately (−2.3, 2.3) to (−2.7, 3.8) METs (2). It is important to note that there are still limitations in using HR to estimate the quantity and quality of PA and EE. These include the effects of ambient temperature, emotional state, hydration status, type of contraction and size of muscle mass involvement (4,7,14,20,24).

In conclusion, from the data collected in this study HR was shown to be a moderate physiological indicator of $\dot{V}O_2$, and thus EE, during a wide range of "lifestyle activities." After adjusting for age and fitness level, HR was a strong predictor of EE ($r = 0.87$, SEE = 0.76 METs). This finding could have great practical significance in large-scale studies. Therefore, HR monitoring warrants further exploration, either individually or in conjunction with other quantitative assessment methods, as a tool for the measurement of habitual PA in free-living individuals.

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