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Abstract

The aims of this study were to quantify the effects of factors such as mode of exercise, body composition and training on the relationship between heart rate and physical activity energy expenditure (measured in kJ x [min.sup.-1]) and to develop prediction equations for energy expenditure from heart rate. Regularly exercising individuals (n = 115; age 18-45 years, body mass 47-120 kg) underwent a test for maximal oxygen uptake (V[O.sub.2max] test), using incremental protocols on either a cycle ergometer or treadmill; V[O.sub.2max] ranged from 27 to 81 x ml [kg.sup.-1] x [min.sup.-1]. The participants then completed three steady-state exercise stages on either the treadmill (10 min) or the cycle ergometer (15 min) at 35%, 62% and 80% of V[O.sub.2max], corresponding to 57%, 77% and 90% of maximal heart rate. Heart rate and respiratory exchange ratio data were collected during each stage. A mixed-model analysis identified gender, heart rate, weight, V[O.sub.2max] and age as factors that best predicted the relationship between heart rate and energy expenditure. The model (with the highest likelihood ratio) was used to estimate energy expenditure. The correlation coefficient (r) between the measured and estimated energy expenditure was 0.913. The model therefore accounted for 83.3% ([R.sup.2]) of the variance in energy expenditure in this sample. Because a measure of fitness, such as V[O.sub.2max], is not always available, a model without V[O.sub.2max] included was also fitted. The correlation coefficient between the measured energy expenditure and estimates from the mixed model without V[O.sub.2max] was 0.857. It follows that the model without a fitness measure accounted for 73.4% of the variance in energy expenditure in this sample. Based on these results, we conclude that it is possible to estimate physical activity energy expenditure from heart rate in a group of individuals with a great deal of accuracy, after adjusting for age, gender, body mass and fitness.

Keywords: Energy expenditure, physical activity, prediction equations

Introduction

During moderate physical activity, there is a linear relationship between heart rate and oxygen consumption. This heart rate--oxygen consumption relationship is subject to both intra- and inter-individual variability. Heart rate may be partially dissociated from energy expenditure by factors such as emotion, posture and environmental conditions (Hebestreit & Bar-Or, 1998). The relationship between heart rate and energy expenditure is linear only within a relatively narrow range of approximately 90-150 beats x [min.sup.-1] (the so-called "flex heart rate") during physical activity (Ceesay et al., 1989; Rennie, Hennings, Mitchell, & Wareham, 2001; Spurr et al., 1988). During light activity or inactivity, there is almost no slope to the relationship between heart rate and energy expenditure, and for the purpose of measuring energy expenditure from heart rate it is assumed that energy expenditure is equal to resting energy expenditure (Rennie et al., 2001). A non-linear, discontinuous function has been found to be more accurate than a linear relationship in predicting physical activity energy expenditure from heart rate (Li, Deurenberg, & Hautvast, 1993).

Heart rate monitoring, for estimating free-living energy expenditure, has been extensively validated using indirect calorimetry, doubly labelled water and whole-room respirometry, and reported differences between measures range from -20% to +25% (Luke, Maki, Barkey, Cooper, & McGee, 1997). In large groups of people, heart rate monitoring provides one of the most efficient and economical means of estimating energy expenditure. In addition, heart rate monitoring provides useful insights into the type of activity being undertaken over the measurement period. Other assessment methods, such as doubly labelled water, can only convey the total amount of physical activity measured, whereas heart rate monitoring provides physiological information about the type of activities being performed and describes the nature of day-to-day variability in energy expenditure (Hebestreit & Bar-Or, 1998; Luke et al., 1997). While whole-room respirometry and indirect calorimetry provide physiological information about the nature of the activity being performed, these tools are not only costly to maintain, but often take the participant out of his or her natural environment for the duration of the measurement period (Luke et al., 1997).

In most previous studies investigating the use of heart rate in the prediction of energy expenditure, individual calibration of the heart rate-energy expenditure relationship was performed (Ceesay et al., 1989; Li et al., 1993; Luke et al., 1997; Spurr et al., 1988). Individual calibration requires that each participant complete a progressive exercise test, during which time heart rate is simultaneously measured, along with indirect calorimetry to estimate energy expenditure. Two recent studies have investigated free-living energy expenditure with heart rate monitoring utilizing prediction equations, generated on large samples of individuals, instead of an individual calibration test (Hiilloskorpi et al., 1999; Rennie et al., 2001). Hiilloskorpi et al. (1999) developed a prediction equation for energy expenditure from heart rate, using multiple regression analysis, on a sample of 87 healthy, active men and women. Factors found to have a significant interaction with energy expenditure included age, weight and gender. Mode of exercise (cycling versus running) did not contribute significantly to the model.

In a more recent study, Rennie et al. (2001) developed a prediction model using a sample of 789 individuals. Factors found to have a significant effect on the relationship between heart rate and energy expenditure included sitting heart rate in addition to age, weight and gender. These variables were used to predict the slope and the intercept of the regression line between energy expenditure and heart rate. This energy expenditure equation was then further validated on an independent sample of 97 individuals and found to have a correlation coefficient (r) of 0.73. Rennie et al. (2001) demonstrated the utility of developing equations for estimating physical activity energy expenditure, from the heart rate-energy expenditure relationship in large, representative samples of individuals, with reasonable accuracy and the potential for wide application in epidemiological studies.

The main aim of the present study was to further characterize the factors that influence the relationship between energy expenditure and heart rate during moderate to vigorous activity in regularly exercising persons. A second aim was to develop a prediction equation for energy expenditure from heart rate, adjusting for these factors.

Methods

Part 1: Developing the energy expenditure prediction equation

Participants. The participants were recruited from a local fitness centre, group-based exercise programmes, running clubs and cycle races. Altogether, 127 regularly exercising men and women volunteered for the study (of which 115 had complete data). The participants were familiar either with a cycle ergometer or motor-driven treadmill, and ranged in age from 19 to 45 years. They were free from any known cardiac or metabolic disorders and were not currently taking any chronic medication. The physical characteristics of the participants are presented in Table I. The participants were tested on two occasions, after self-selecting the mode of exercise (cycle ergometer, n = 69; treadmill, n = 46). The Ethics and Research Committee of the University of Cape Town, Faculty of Health Sciences, approved the study and informed consent was obtained from all participants before the trials began.

A second sample of regularly exercising individuals (n = 17) was subsequently recruited, independent of the first sample, to test the validity of the prediction model. The second sample was recruited from a local fitness centre, and represented a wide range of ages (21-53 years), weights (51105 kg) and fitness (V[O.sub.2max] = 34-74.3 ml x [kg.sup.-1] x [min.sup.1]).

Body composition. Body fatness was expressed as the sum of seven skinfolds (biceps, triceps, subscapular, suprailiac, anterior thigh, abdominal and medial calf). Percentage body fat was estimated using the equations of Dumin and Womersley (1974).

Maximal oxygen consumption. During the first visit to the laboratory, maximal oxygen consumption (V[O.sub.2max), maximal heart rate, and peak power output or peak treadmill running speed were measured. Maximal oxygen uptake was measured during either a progressive treadmill or cycle test to exhaustion. During the treadmill test, the starting treadmill speed was 12 km x [h.sup.-1] for the men and 10 km x [h.sup.-1] for the women, and it was increased by 0.5 km x [h.sup.-1] every 30 s until volitional exhaustion, as described previously (Noakes, Myburgh, & Schall, 1990). In the cycle test to exhaustion, participants were tested on an electronically braked cycle ergometer (Lode, Gronigen, The Netherlands). Each participant started cycling at an exercise intensity of 3.33 W x [kg.sup.-1] body weight for 150 s, after which the work rate was increased by 50 W for a further 150 s. The exercise intensity was then increased by 25 W every 150 s up to the point of exhaustion (Hawley & Noakes, 1992). Maximal heart rate was defined as that heart rate achieved at the point of exhaustion. During both the treadmill and cycle tests, the participants wore a facemask attached to an Oxycon Alpha automated gas analyser (Oxycon, Jaeger, The Netherlands). Before each test, the gas analyser was calibrated using a Hans Rudolph 5530 3-litre syringe and a two-point calibration technique, using a 5% C[O.sub.2]/95% [N.sub.2] gas mixture and fresh air. The rate of oxygen consumption (V[O.sub.2]), rate of carbon dioxide production (VC[O.sub.2]) and the respiratory exchange ratio (RER) were calculated using conventional equations (Weir, 1990). Peak power output and peak treadmill running speed were defined as the workload at which the participant could no longer maintain the pace of the treadmill or maintain a cadence of 70 rev x [min.sup.-1].

Submaximal testing and estimation of energy expenditure. The participants returned to the laboratory within a week and performed a submaximal test. The cycle ergometer submaximal test protocol consisted of three consecutive workloads, each lasting 15 min, during which the participants cycled at 25%, 55% and 70% of the previously determined peak power output, corresponding to 41%, 63% and 80% of V[O.sub.2max] respectively. The submaximal treadmill protocol consisted of three consecutive workloads, each lasting 10 min, at 35%, 50% and

70% (corresponding to approximately 41%, 63% and 80% of V[O.sub.2max] respectively) of previously determined peak treadmill running speed. Minute-to-minute heart rate was recorded using the Polar Vantage heart rate monitor (Polar Electro, Finland) and respiratory exchange measurements (V[O.sub.2] and VC[O.sub.2]) were collected and used to estimate energy expenditure, based on the equations of Weir (1990), during the last 5 min of each of the stages. The submaximal heart rate data from the last 5 min of each stage were used to subsequently calculate predicted energy expenditure on the basis of individual regression equations. Factors that were significantly correlated with heart rate or V[O.sub.2] were used in the model to predict energy expenditure.

Part 2: Validation of prediction model on an independent sample

For the purpose of validation, the energy expenditure values from a 20-min self-selected cardiovascular session were predicted on an independent sample of individuals, recruited from a local fitness centre. These participants were instructed to choose either a single 20-min cardiovascular workout or two 10-min exercise bouts.

Participants. The 17 participants (9 males, 8 females) were free from known cardiovascular and metabolic disorders and took part in some form of cardiovascular physical activity at least three times a week. The participants met the inclusion criteria of the original study and their physical characteristics are presented in Table II.

Body composition and maximal test to exhaustion. The participants reported to the laboratory on two different occasions within 7 days. During their first visit, the participants had their body composition measured using the near infrared reactance technique (Futrex Inc., Gaithersburg, MD, USA). They then performed a maximal test to exhaustion on an electronically braked cycle ergometer (Lode, Gronigen, The Netherlands) as previously described (Hawley & Noakes, 1992). During the test, oxygen consumption and carbon dioxide productions were measured as described above.

Estimation of physical activity energy expenditure. During the second visit, the participants reported to the laboratory in a 2-h post-prandial state. They were instructed not to engage in any strenuous physical activity during the preceding 24 h. All participants completed a 20-min cardiovascular exercise session as part of an independent study in progress. The cardiovascular component was performed following a 5-min warm-up consisting of 23 min of walking and 2-3 min of light jogging. The participants then chose to either complete one 20min continuous cardiovascular exercise session or two 10-min sessions on a self-selected piece of fitness centre equipment. Throughout the exercise session, the participants' heart rate, V[O.sub.2] and VC[O.sub.2] were monitored continuously using the [K4b.sup.2] portable gas analyser (Cosmed, Italy). Minute-by-minute energy expenditure (kJ x [min.sup.-1]) was then determined using the non-protein caloric equivalents for oxygen. Before each test, the portable gas analyser was calibrated using a Hans Rudolph 5530 3-1itre syringe and a two-point calibration technique, using a 5% C[O.sub.2].sub.1]/16% [0.sub.2] gas mixture and fresh air. The analyser outputs were processed to calculate breath-by-breath ventilation, V[O.sub.2], VC[O.sub.2] and the respiratory exchange ratio using conventional equations (Weir, 1990).

Statistical analysis

Initially, 127 individuals volunteered to participate in the study. The final sample size was 115 because of incomplete heart rate and V[O.sub.2max] for 12 participants. The initial exploratory data analyses to determine factors that may have significantly contributed to the relationship between heart rate and energy expenditure included Box plots and scatter plots for all variables (not shown).

Univariate (means, standard deviations) and bivariate (correlation coefficients) summary statistics were then calculated for all variables.

Based on these analyses, we fitted a mixed model for predicting energy expenditure. The factors gender, weight, age and V[O.sub.2max] were modelled as fixed effects, and participants as random effects, with three repeated measurements of energy expenditure (and fixed heart rate) for each participant. In the model, the covariance matrix between the measurements for each participant was unstructured and compound symmetry was assumed for the covariances between participants.

A second mixed model was fitted under the rationale that, in certain settings, a test of maximal oxygen consumption might be impractical or not available. The second model included all the variables and assumptions in the original model except V[O.sub.2max]. For inner validation, both models were tested on an independent sample of participants (n = 17), who completed 20 min of cardiovascular exercise.

The initial exploratory analyses were performed using the Statistica data analysis software system (version 6.1, Statsoft, Southern Africa Inc., 2002). Statistical modelling was done with SAS[R] Proprietary Software Release 8.2 (USA).

Results

Characteristics of sample used to develop the prediction equation

The characteristics of the participants are presented in Table I. The participants represented a wide range of morphology and fitness: age 19-45 years of age, body weight 47-116 kg, percentage body fat 4.8-37.8% and V[O.sub.2max] 27-81 ml x [kg.sup.-1] x [min.sup.-1]. There were no differences in mean age, weight, percentage body fat or V[O.sub.2max] between the participants who underwent treadmill testing versus those that underwent cycle ergometer testing. There were significant differences in weight, percentage body fat and V[O.sub.2max] between the sexes (Table I, $P < 0.00001$).

Characteristics of sample used for inner validation

The characteristics of the participants are presented in Table II. The participants in this sample were similar to those used in the original study and represented a broad range in body composition. Percentage body fat ranged from 9.4 to 21.6% in the men and from 21.6 to 30.6 % in the women. Similarly, there was a wide range in the performance data, with V[O.sub.2max] ranging from 38.7 to 73.8 ml x [kg-.sup.-1] x [min.sup.-1] in the men and from 34.3 to 49.6 ml x [kg.sup.-1] x [min.sup.-1] in the women.

The participants in both samples were equally matched for age and weight. The participants (males and females combined) in the original study were slightly fitter (mean V[O.sub.2max] 53.5 [+ or -] 0.5 ml. [kg-.sup.-1]. [min.sup.-1]) than those who took part in the validation study (mean V[O.sub.2max] 48.1 [+ or -] 0.5 ml x [kg.sup.-1] x [min.sup.-1]); this difference was not statistically significant.

Prediction equations of energy expenditure from heart rate: Mixed-model analysis

A mixed model was used to derive the following equation for predicting physical activity energy expenditure (EE):

EE = -59.3954 + gender x (-36.3781 + 0.271 x age + 0.394 x weight + 0.404 V[O.sub.2max] + 0.634x heart rate) + (1 - gender) x (0.274 x age + 0.103x weight + 0.380x V[O.sub.2max] + 0.450 x heart rate) where gender = 1 for males and 0 for females. Table III shows the above model in a different format. The likelihood ratio test for goodness-of-fit [chi square] = 262.73 on five degrees of freedom with P < 0.0001. The results of type III tests for the fixed effects in the mixed model are presented in Table IV. The degrees of freedom for the F-tests were calculated using Satterthwaite's method.

In Figure 1, the measured energy expenditure is regressed against estimated energy expenditure. The correlation coefficient (r) is 0.913, so [R.sup.2] = 83.3% of the variation in measured energy expenditure in the sample is explained by the model.

[FIGURE 1 OMITTED]

A second model, which contained no measure of fitness, was also fitted. The final prediction equation for energy expenditure using age, gender, weight and heart rate was:

EE = gender x (-55.0969 + 0.6309 x heart rate + 0.1988 x weight + 0.2017 x age) + (1 - gender) x (-20.4022 + 0.4472 x heartrate - 0.1263 x weight + 0.074 x age)

where gender = 1 for males and 0 for females. Table V shows the above model in a different format. The likelihood ratio test for goodness-of-fit [chi square] = 360.68 on five degrees of freedom with P < 0.0001. The results of type III tests for the fixed effects in the mixed model are given in Table VI. The degrees of freedom for the F-tests were calculated using Satterthwaite's method.

In Figure 2, the measured energy expenditure is regressed against estimated energy expenditure. The coefficient of correlation 0.857, so [R.sup.2] = 73.4% of the variation in measured energy expenditure in the sample is explained by the model.

[FIGURE 2 OMITTED]

Independent sample analysis for inner validation

Data from an independent sample of 17 participants (8 females, 9 males) were used to validate both models. Predicted energy expenditure using the first model, which included a measure of fitness (V[O.sub.2max]), correlated with measured energy expenditure during self-selected cardiovascular fitness training ($r = 0.836$, $P < 0.0001$; Figure 3). Using the second model for measuring energy expenditure, with no measure of fitness, the correlation coefficient was 0.77 ($P < 0.0001$) (Figure 4).

[FIGURE 3-4 OMITTED]

Agreement

Because we used a mixed model (with random participant effects), we had to use maximum likelihood estimation instead of least squares. The result is that even the estimates for the initial sample which was used to develop the equations are slightly biased. The bias of the estimates and their random variation for the four sets of estimates are summarized in Table VII. The bias is the difference between the predicted and the corresponding actual value of energy expenditure, and the 95% limits of absolute agreement were calculated as described in Atkinson and Nevill (1998). It is interesting to note that the bias in the initial sample is on average in the opposite direction to that for the validation sample. The fact that the agreement limits become wider down the table is completely logical. We believe that these limits are narrow enough for the underlying models to be of practical use.

Discussion

In this study, we demonstrated that physical activity energy expenditure during moderate- to high-intensity exercise may be predicted with good accuracy in a group of individuals varying widely in age, fitness and morphology, without the need for individual calibration. This study denotes an improvement over existing studies in the estimation of physical activity energy expenditure using heart rate monitoring. The proposed model (using heart rate, age, weight, gender and level of fitness V[O.sub.2max])) accounted for 70% of the variation in observed energy expenditure in an independent sample of people completing a self-selected 20-min cardiovascular exercise session.

Previous studies (Li et al., 1993; Rutgers, Klijn, & Deurenberg, 1997) have cited poor agreement between energy expenditure estimated using heart rate monitoring and measured energy expenditure. These prediction equations were developed on small samples, not representative of the population to which the equation was to be applied. Rutgers et al. (1997) developed a prediction equation based on the heart rate and energy expenditure data acquired from 13 elderly individuals. The authors concluded that the use of heart rate monitoring to measure energy expenditure was inaccurate over 3 days of measurement, citing large discrepancies between energy expenditure estimation using the individual calibration curve and a group curve. Li et al. (1993) also reported poor agreement for the estimation of energy expenditure using heart rate monitoring between group and individually derived estimates. Once again, this sample was relatively small, consisting of only 40 persons.

The current study represents an improvement over existing studies (Hiilloskorpi et al., 1999; Rennie et al., 2001) that used heart rate monitoring to estimate physical activity energy expenditure, without individual calibration. Previously, Rennie et al. (2001) used the variables that significantly interacted with energy expenditure to predict the slope, intercept and the heart rate flex point for measured versus predicted physical activity energy expenditure. In that study, the variables of sitting heart rate, age, weight and gender were found to have a significant impact on the slope, intercept and heart rate flex point. These investigators were then able to use the slope and intercept of the linear model to place 98% of the participants in their sample in either the same or adjacent quartiles for the measured and estimated physical activity levels. Their model has implications for physical activity classification in epidemiological models. In the current study, we derived linear equations, based on mixed-model analyses. These equations yield predictions that correlate significantly with the test sample as well as the independent validation sample.

Previously, Hiilloskorpi et al. (1999) developed an equation to predict energy expenditure using the variables of heart rate, age, weight and gender. They showed that the mode of exercise, cycling versus running, did not significantly affect the final prediction of energy expenditure. We also found that the mode of exercise did not affect the estimation of energy expenditure, and therefore suggest that the proposed equation may be used for both running and cycling activities. During our inner validation study, we even found good agreement with other models of continuous activity, such as stationary rowing ergometry and stationary stair-climbing activities.

Hiilloskorpi et al. (1999) did not include any measure of physical fitness or V[O.sub.2max] in their prediction equation, citing a need to produce an equation for estimating energy expenditure independent of laboratory testing. We found that when a measure of the level of cardiorespiratory fitness such as V[O.sub.2max] is included, the accuracy of the prediction improved. The correlation coefficients (r) of the study sample were 0.913 for the model V[O.sub.2max] with and 0.857 for the model without V[O.sub.2max]. The increase in variation explained by the model including V[O.sub.2max] is 83.4%-

73.4% = 10%. The correlation coefficients of the validation sample were 0.836 for the model with V[O.sub.2max] and 0.77 for the model without V[O.sub.2max]. The increase in variation explained by the model including V[O.sub.2max] is approximately 10%. It is well known that training results in adaptations in the heart rate response to increasing workloads (Meijer, Westerterp, & Verstappen, 1999; Wilmore et al., 1996). Therefore, it is not surprising that an indirect measure of cardiorespiratory fitness improves the accuracy of the prediction of energy expenditure from heart rate. This finding is in line with the study of Rennie et al. (2001), in which sitting heart rate was found to play a significant role in the prediction of energy expenditure from heart rate monitoring. Rennie et al. (2001) proposed that resting heart rate when sitting was a useful proxy measurement for fitness, since previous studies have found an inverse association between resting tachycardia and maximal exercise capacity (Blair, Kannel, Kohl, Goodyear, & Wilson, 1989), as well as a positive relationship between regular participation in physical activity and lower resting heart rate, independent of age (Steinhaus et al., 1988).

Hiilloskorpi et al. (1999) found that including age in the regression model did not significantly improve the variance. This is at odds with the current study, as we found that age did contribute significantly to the final mixed model. This difference may partly be explained by differences in sample characteristics. Hiilloskorpi et al. (1999) acknowledges a relatively narrow age range, with few participants older than 50 years or younger than 25 years. In our study, the mean age of the 72 men was 31 years (range 19-50 years) and that of the 43 women was 30 years (range 22-44 years). In the study of Hiilloskorpi et al. (1999), the mean age of the 45 men was 40 years and that of the 43 women was 38 years. Their participants were notably older than those in the current study. In addition to the age discrepancies between the two studies, there were also discrepancies between the fitness of the two samples. In the current study, the mean V[O.sub.2max] for the men was 59.2 ml x [min.sup.-1] x [kg.sup.-1] and for the women it was 45.7 59.2 ml x [min.sup.-1] x [kg.sup.-1]; in the study of Hiilloskorpi et al. (1999), the mean values were 48.5 and 39.5 ml x [min.sup.-1] x [kg.sup.-1] for the men and women respectively. These demographic differences may partly account for the differences found between the two prediction models. Rennie et al. (2001) also found that age impacted in the regression model of physical activity energy expenditure from heart rate. It may be argued that the sample used to generate the prediction equation comprised a well-trained group of individuals, but we feel that they represented a typical fitness centre population. Maximal oxygen uptake ranged from 27.0 to 64.1 ml x [min.sup.-1] x [kg.sup.-1] in the women and from 38.0 to 81.4 ml x [min.sup.-1] x [kg.sup.-1] in the men. It was the intention of the present study to apply this equation to the general exercising population and, as a result, our recruitment focused on a local fitness centre, amateur running clubs and cycling races. While our average fitness levels were unlike those presented in both Hiilloskorpi et al. (1999) and Rennie et al. (2001), we have demonstrated that the inclusion of V[O.sub.2max], as a proxy for fitness, improves the predictability of our group-based equation.

While many other studies (Hiilloskorpi et al., 1999; Li et al., 1993; Rennie et al., 2001; Strath et al., 2000) have used similar approaches to develop prediction equations without individual calibration, not all of them (Hiilloskorpi et al., 1999; Strath et al., 2000) used an independent sample for inner validation of the developed model and, in some cases, did not report inner validation of the developed model (Strath et al., 2000) or used the same sample for which the original prediction equation was developed (Hiilloskorpi et al., 1999). This may lead to elevated levels of agreement between the prediction models and measured estimates, due to the homogeneous nature of samples. For example, Strath et al. (2000) estimated physical activity during moderate-intensity exercise using heart rate monitoring and reported good agreement ($r = 0.87$) between measured and estimated energy expenditure; however, in this study, no inner validation was performed on an independent sample of participants. Conversely, Rennie et al. (2001) validated a prediction equation for physical activity levels, developed on a sample of 789 individuals, on a smaller subset of 97 individuals. During this inner validation, 98% of the subset was placed in the same or adjacent quartiles during comparison of measured and estimated physical activity levels. In the current study, we found good agreement on an independent sample of participants. The prediction equation explained 71% of the variance in estimated energy expenditure in an independent sample, during self-selected cardiovascular exercise training.

Finally, for practical application the proposed equations represent an improvement in the estimation of energy expenditure from heart rate over existing equations. They may be used in large population-based studies for health purposes. Further research is needed on the simultaneous measurement of physical activity energy expenditure and heart rate. Predictive equations that estimate energy expenditure for health research and promotion are required for a wider variety of activities, particularly for intermittent activity or activity conducted at lower intensities.

Table I. Characteristics of the sample used to develop the prediction equation (mean [+ or -] s)

	Treadmill	
	Men (n = 22)	Women (n = 24)
Age (years)	30 [+ or -] 7	30 [+ or -] 6
Weight (kg) *	76 [+ or -] 10	66 [+ or -] 11
Percent body fat *	14.5 [+ or -] 4.8	26.8 [+ or -] 5.2
V[O.sub.2max] (ml x		

[kg.sup.-1] x [min.sup.-1]) *	65.0 [+ or -] 8.6	49.0 [+ or -] 9.7
Maximal heart rate (beats x [min.sup.-1])	189 [+ or -] 9	184 [+ or -] 9

Cycle ergometer

	Men (n = 50)	Women (n = 19)
Age (years)	31 [+ or -] 6	31 [+ or -] 6
Weight (kg) *	81 [+ or -] 13	62 [+ or -] 6
Percent body fat *	16.6 [+ or -] 4.2	23.1 [+ or -] 5.0
V[O.sub.2max] (ml x [kg.sup.-1] x [min.sup.-1]) *	55.3 [+ or -] 8.3	48.3 [+ or -] 8.1
Maximal heart rate (beats x [min.sup.-1])	187 [+ or -] 11	185 [+ or -] 9

* P < 0.00001, differences between the sexes.

Table II. Characteristics of the sample used for inner validation (mean [+ or -] s)

	Men (n = 9)	Women (n = 8)
Age (years)	29 [+ or -] 8	34 [+ or -] 10
Weight (kg) *	81 [+ or -] 14	62 [+ or -] 9
Percent body fat *	14.8 [+ or -] 5.1	26.0 [+ or -] 3.9
V[O.sub.2max] (ml x [kg.sup.-1]		

x [min.sup.-1]) *   54.3 [+ or -] 11.4   42.4 [+ or -] 5.4
Maximal heart
rate (beats x
[min.sup.-1])   190 [+ or -] 9   178 [+ or -] 15

* P < 0.00001, differences between the sexes.

Table III. The estimates and their standard errors for the fixed effects of the model including fitness

	Men		Women	
Effect	Estimate	Standard error	Estimate	Standard error
Intercept	-95.7735	9.5734	-59.3954	17.1314
Heart rate	0.6344	0.0137	0.4498	0.0165
Weight	0.3942	0.0642	0.1032	0.1166
V[O.sup.2max]	0.4044	0.0837	0.3802	0.1575
Age	0.2713	0.1120	0.2735	0.2087

Table IV. Table with type III analysis for fixed effects of model including fitness

Effect	Degrees of freedom	F-value	P-value
Gender	2, 109	56.05	< 0.0001
Heart rate x gender	2, 125	1444.98	< 0.0001
Weight x gender	2, 100	19.23	< 0.0001
V[O.sub.2max] x gender	2, 101	14.57	< 0.0001
Age x gender	2, 101	3.79	0.0258

Table V. The estimates and their standard errors for the fixed effects of the mixed model without fitness

Effect	Men Estimate	Men Standard error	Women Estimate	Women Standard error
Intercept	-55.0969	5.5780	-20.4022	7.2318
Heart rate	0.6309	0.0137	0.4472	0.0165
Weight	0.1988	0.0619	-0.1263	0.1061
Age	0.2017	0.1180	0.0740	0.1742

Table VI. Results of type III tests for fixed effects of model excluding fitness.

Effect	Degrees of freedom	F-value	P-value
Gender	2, 109	14.43	0.0002
Heart rate x gender	2, 125	1428.63	< 0.0001
Weight x gender	2, 99.9	5.86	0.0039
Age x gender	2, 100	1.55	0.2170

Table VII. Summary of the bias of the energy expenditure (in kJ x [min.sup.-1]) estimates and their random variation for the four sets of estimates

Sample	Model	Mean	Standard deviation
Initial	Including fitness	-1.06	7.83
Initial	No fitness	-5.79	9.85
Validation	Including fitness	8.19	9.19
Validation	No fitness	6.27	9.65

Sample	95% limits of agreement	
Initial	-16.41	14.28

Initial	-25.10	13.52
Validation	-9.83	26.21
Validation	-12.65	25.19

Note: The bias is the difference between the predicted and the corresponding actual value of energy expenditure.

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Abstract

The aims of this study were to quantify the effects of factors such as mode of exercise, body composition and training on the relationship between heart rate and physical activity energy expenditure (measured in kJ x [min.sup.-1]) and to develop prediction equations for energy expenditure from heart rate. Regularly exercising individuals (n = 115; age 18-45 years, body mass 47-120 kg) underwent a test for maximal oxygen uptake (V[O.sub.2max] test), using incremental protocols on either a cycle ergometer or treadmill; V[O.sub.2max] ranged from 27 to 81 x ml [kg.sup.-1] x [min.sup.-1]. The participants then completed three steady-state exercise stages on either the treadmill (10 min) or the cycle ergometer (15 min) at 35%, 62% and 80% of V[O.sub.2max], corresponding to 57%, 77% and 90% of maximal heart rate. Heart rate and respiratory exchange ratio data were collected during each stage. A mixed-model analysis identified gender, heart rate, weight, V[O.sub.2max] and age as factors that best predicted the relationship between heart rate and energy expenditure. The model (with the highest likelihood ratio) was used to estimate energy expenditure. The correlation coefficient (r) between the measured and estimated energy expenditure was 0.913. The model therefore accounted for 83.3% ([R.sup.2]) of the variance in energy expenditure in this sample. Because a measure of fitness, such as V[O.sub.2max], is not always available, a model without V[O.sub.2max] included was also fitted. The correlation coefficient between the measured energy expenditure and estimates from the mixed model without V[O.sub.2max] was 0.857. It follows that the model without a fitness measure accounted for 73.4% of the variance in energy expenditure in this sample. Based on these results, we conclude that it is possible to estimate physical activity energy expenditure from heart rate in a group of individuals with a great deal of accuracy, after adjusting for age, gender, body mass and fitness.

Keywords: Energy expenditure, physical activity, prediction equations

Introduction

During moderate physical activity, there is a linear relationship between heart rate and oxygen consumption. This heart rate--oxygen consumption relationship is subject to both intra- and inter-individual variability. Heart rate may be partially dissociated from energy expenditure by factors such as emotion, posture and environmental conditions (Hebestreit & Bar-Or, 1998). The relationship between heart rate and energy expenditure is linear only within a relatively narrow range of approximately 90-150 beats x [min.sup.-1] (the so-called "flex heart rate") during physical activity (Ceesay et al., 1989; Rennie, Hennings, Mitchell, & Wareham, 2001; Spurr et al., 1988). During light activity or inactivity, there is almost no slope to the relationship between heart rate and energy expenditure, and for the purpose of measuring energy expenditure from heart rate it is assumed that energy expenditure is equal to resting energy expenditure (Rennie et al., 2001). A non-linear, discontinuous function has been found to be more accurate than a linear relationship in predicting physical activity energy expenditure from heart rate (Li, Deurenberg, & Hautvast, 1993).

Heart rate monitoring, for estimating free-living energy expenditure, has been extensively validated using indirect calorimetry, doubly labelled water and whole-room respirometry, and reported differences between measures range from -20% to +25% (Luke, Maki, Barkey, Cooper, & McGee, 1997). In large groups of people, heart rate monitoring provides one of the most efficient and economical means of estimating energy expenditure. In addition, heart rate monitoring provides useful insights into the type of activity being undertaken over the measurement period. Other assessment methods, such as doubly labelled water, can only convey the total amount of physical activity measured, whereas heart rate monitoring provides physiological information about the type of activities being performed and describes the nature of day-to-day variability in energy expenditure (Hebestreit & Bar-Or, 1998; Luke et al., 1997). While whole-room respirometry and indirect calorimetry provide physiological information about the nature of the activity being performed, these tools are not only costly to maintain, but often take the participant out of his or her natural environment for the duration of the measurement period (Luke et al., 1997).

In most previous studies investigating the use of heart rate in the prediction of energy expenditure, individual calibration of the heart rate-energy expenditure relationship was performed (Ceesay et al., 1989; Li et al., 1993; Luke et al., 1997; Spurr et al., 1988). Individual calibration requires that each participant complete a progressive exercise test, during which time heart rate is simultaneously measured, along with indirect calorimetry to estimate energy expenditure. Two recent studies have investigated free-living energy expenditure with heart rate monitoring utilizing prediction equations, generated on large samples of individuals, instead of an individual calibration test (Hiilloskorpi et al., 1999; Rennie et al., 2001). Hiilloskorpi et al. (1999) developed a prediction equation for energy expenditure from heart rate, using multiple regression analysis, on a sample of 87 healthy, active men and women. Factors found to have a significant interaction with energy expenditure included age, weight and gender. Mode of exercise (cycling versus running) did not contribute significantly to the model.

In a more recent study, Rennie et al. (2001) developed a prediction model using a sample of 789 individuals. Factors found to have a significant effect on the relationship between heart rate and energy expenditure included sitting heart rate in addition to age, weight and gender. These variables were used to predict the slope and the intercept of the regression line between energy expenditure and heart rate. This energy expenditure equation was then further validated on an independent sample of 97 individuals and found to have a correlation coefficient (r) of 0.73. Rennie et al. (2001) demonstrated the utility of developing equations for estimating physical activity energy expenditure, from the heart rate-energy expenditure relationship in large, representative samples of individuals, with reasonable accuracy and the potential for wide application in epidemiological studies.

The main aim of the present study was to further characterize the factors that influence the relationship between energy expenditure and heart rate during moderate to vigorous activity in regularly exercising persons. A second aim was to develop a prediction equation for energy expenditure from heart rate, adjusting for these factors.

Methods

Part 1: Developing the energy expenditure prediction equation

Participants. The participants were recruited from a local fitness centre, group-based exercise programmes, running clubs and cycle races. Altogether, 127 regularly exercising men and women volunteered for the study (of which 115 had complete data). The participants were familiar either with a cycle ergometer or motor-driven treadmill, and ranged in age from 19 to 45 years. They were free from any known cardiac or metabolic disorders and were not currently taking any chronic medication. The physical characteristics of the participants are presented in Table I. The participants were tested on two occasions, after self-selecting the mode of exercise (cycle ergometer, n = 69; treadmill, n = 46). The Ethics and Research Committee of the University of Cape Town, Faculty of Health Sciences, approved the study and informed consent was obtained from all participants before the trials began.

A second sample of regularly exercising individuals (n = 17) was subsequently recruited, independent of the first sample, to test the validity of the prediction model. The second sample was recruited from a local fitness centre, and represented a wide range of ages (21-53 years), weights (51105 kg) and fitness (V[O.sub.2max] = 34-74.3 ml x [kg.sup.-1] x [min.sup.1]).

Body composition. Body fatness was expressed as the sum of seven skinfolds (biceps, triceps, subscapular, suprailiac, anterior thigh, abdominal and medial calf). Percentage body fat was estimated using the equations of Dumin and Womersley (1974).

Maximal oxygen consumption. During the first visit to the laboratory, maximal oxygen consumption (V[O.sub.2max), maximal heart rate, and peak power output or peak treadmill running speed were measured. Maximal oxygen uptake was measured during either a progressive treadmill or cycle test to exhaustion. During the treadmill test, the starting treadmill speed was 12 km x [h.sup.-1] for the men and 10 km x [h.sup.-1] for the women, and it was increased by 0.5 km x [h.sup.-1] every 30 s until volitional exhaustion, as described previously (Noakes, Myburgh, & Schall, 1990). In the cycle test to exhaustion, participants were tested on an electronically braked cycle ergometer (Lode, Gronigen, The Netherlands). Each participant started cycling at an exercise intensity of 3.33 W x [kg.sup.-1] body weight for 150 s, after which the work rate was increased by 50 W for a further 150 s. The exercise intensity was then increased by 25 W every 150 s up to the point of exhaustion (Hawley & Noakes, 1992). Maximal heart rate was defined as that heart rate achieved at the point of exhaustion. During both the treadmill and cycle tests, the participants wore a facemask attached to an Oxycon Alpha automated gas analyser (Oxycon, Jaeger, The Netherlands). Before each test, the gas analyser was calibrated using a Hans Rudolph 5530 3-litre syringe and a two-point calibration technique, using a 5% C[O.sub.2]/95% [N.sub.2] gas mixture and fresh air. The rate of oxygen consumption (V[O.sub.2]), rate of carbon dioxide production (VC[O.sub.2]) and the respiratory exchange ratio (RER) were calculated using conventional equations (Weir, 1990). Peak power output and peak treadmill running speed were defined as the workload at which the participant could no longer maintain the pace of the treadmill or maintain a cadence of 70 rev x [min.sup.-1].

Submaximal testing and estimation of energy expenditure. The participants returned to the laboratory within a week and performed a submaximal test. The cycle ergometer submaximal test protocol consisted of three consecutive workloads, each lasting 15 min, during which the participants cycled at 25%, 55% and 70% of the previously determined peak power output, corresponding to 41%, 63% and 80% of V[O.sub.2max] respectively. The submaximal treadmill protocol consisted of three consecutive workloads, each lasting 10 min, at 35%, 50% and 70% (corresponding to approximately 41%, 63% and 80% of V[O.sub.2max] respectively) of previously determined peak treadmill running speed. Minute-to-minute heart rate was recorded using the Polar Vantage heart rate monitor (Polar Electro, Finland) and respiratory exchange measurements (V[O.sub.2] and VC[O.sub.2]) were collected and used to estimate energy expenditure, based on the equations of Weir (1990), during the last 5 min of each of the stages. The submaximal heart rate data from the last 5 min of each stage were used to subsequently calculate predicted energy expenditure on the basis of individual regression equations. Factors that were significantly correlated with heart rate or V[O.sub.2] were used in the model to predict energy expenditure.

Part 2: Validation of prediction model on an independent sample

For the purpose of validation, the energy expenditure values from a 20-min self-selected cardiovascular session were predicted on an independent sample of individuals, recruited from a local fitness centre. These participants were instructed to choose either a single 20-min cardiovascular workout or two 10-min exercise bouts.

Participants. The 17 participants (9 males, 8 females) were free from known cardiovascular and metabolic disorders and took part in some form of cardiovascular physical activity at least three times a week. The participants met the inclusion criteria of the original study and their physical characteristics are presented in Table II.

Body composition and maximal test to exhaustion. The participants reported to the laboratory on two different occasions within 7 days. During their first visit, the participants had their body composition measured using the near infrared reactance technique (Futrex Inc., Gaithersburg, MD, USA). They then performed a maximal test to exhaustion on an electronically braked cycle ergometer (Lode, Gronigen, The Netherlands) as previously described (Hawley & Noakes, 1992).

During the test, oxygen consumption and carbon dioxide productions were measured as described above.

Estimation of physical activity energy expenditure. During the second visit, the participants reported to the laboratory in a 2-h post-prandial state. They were instructed not to engage in any strenuous physical activity during the preceding 24 h. All participants completed a 20-min cardiovascular exercise session as part of an independent study in progress. The cardiovascular component was performed following a 5-min warm-up consisting of 23 min of walking and 2-3 min of light jogging. The participants then chose to either complete one 20min continuous cardiovascular exercise session or two 10-min sessions on a self-selected piece of fitness centre equipment. Throughout the exercise session, the participants' heart rate, V[O.sub.2] and VC[O.sub.2] were monitored continuously using the [K4b.sup.2] portable gas analyser (Cosmed, Italy). Minute-by-minute energy expenditure (kJ x [min.sup.-1]) was then determined using the non-protein caloric equivalents for oxygen. Before each test, the portable gas analyser was calibrated using a Hans Rudolph 5530 3-1itre syringe and a two-point calibration technique, using a 5% C[O.sub.2].sub.1]/16% [0.sub.2] gas mixture and fresh air. The analyser outputs were processed to calculate breath-by-breath ventilation, V[O.sub.2], VC[O.sub.2] and the respiratory exchange ratio using conventional equations (Weir, 1990).

Statistical analysis

Initially, 127 individuals volunteered to participate in the study. The final sample size was 115 because of incomplete heart rate and V[O.sub.2max] for 12 participants. The initial exploratory data analyses to determine factors that may have significantly contributed to the relationship between heart rate and energy expenditure included Box plots and scatter plots for all variables (not shown). Univariate (means, standard deviations) and bivariate (correlation coefficients) summary statistics were then calculated for all variables.

Based on these analyses, we fitted a mixed model for predicting energy expenditure. The factors gender, weight, age and V[O.sub.2max] were modelled as fixed effects, and participants as random effects, with three repeated measurements of energy expenditure (and fixed heart rate) for each participant. In the model, the covariance matrix between the measurements for each participant was unstructured and compound symmetry was assumed for the covariances between participants.

A second mixed model was fitted under the rationale that, in certain settings, a test of maximal oxygen consumption might be impractical or not available. The second model included all the variables and assumptions in the original model except V[O.sub.2max]. For inner validation, both models were tested on an independent sample of participants (n = 17), who completed 20 min of cardiovascular exercise.

The initial exploratory analyses were performed using the Statistica data analysis software system (version 6.1, Statsoft, Southern Africa Inc., 2002). Statistical modelling was done with SAS[R] Proprietary Software Release 8.2 (USA).

Results

Characteristics of sample used to develop the prediction equation

The characteristics of the participants are presented in Table I. The participants represented a wide range of morphology and fitness: age 19-45 years of age, body weight 47-116 kg, percentage body fat 4.8-37.8% and V[O.sub.2max] 27-81 ml x [kg.sup.-1] x [min.sup.-1]. There were no differences in mean age, weight, percentage body fat or V[O.sub.2max] between the participants who underwent treadmill testing versus those that underwent cycle ergometer testing. There were significant differences in weight, percentage body fat and V[O.sub.2max] between the sexes (Table I, P < 0.00001).

Characteristics of sample used for inner validation

The characteristics of the participants are presented in Table II. The participants in this sample were similar to those used in the original study and represented a broad range in body composition. Percentage body fat ranged from 9.4 to 21.6% in the men and from 21.6 to 30.6 % in the women. Similarly, there was a wide range in the performance data, with V[O.sub.2max] ranging from 38.7 to 73.8 ml x [kg-.sup.-1] x [min.sup.-1] in the men and from 34.3 to 49.6 ml x [kg.sup.-1] x [min.sup.-1] in the women.

The participants in both samples were equally matched for age and weight. The participants (males and females combined) in the original study were slightly fitter (mean V[O.sub.2max] 53.5 [+ or -] 0.5 ml. [kg-.sup.-1]. [min.sup.-1]) than those who took part in the validation study (mean V[O.sub.2max] 48.1 [+ or -] 0.5 ml x [kg.sup.-1] x [min.sup.-1]); this difference was not statistically significant.

Prediction equations of energy expenditure from heart rate: Mixed-model analysis

A mixed model was used to derive the following equation for predicting physical activity energy expenditure (EE):

EE = -59.3954 + gender x (-36.3781 + 0.271 x age + 0.394 x weight + 0.404 V[O.sub.2max] + 0.634x heart rate) + (1 - gender) x (0.274 x age + 0.103x weight + 0.380x V[O.sub.2max] + 0.450 x heart rate) where gender = 1 for males and 0 for females. Table III shows the above model in a different format. The likelihood ratio test for goodness-of-fit [chi square] = 262.73 on five degrees of freedom with P < 0.0001. The results of type III tests for the fixed effects in the mixed model are presented in Table IV. The degrees of freedom for the F-tests were calculated using Satterthwaite's method.

In Figure 1, the measured energy expenditure is regressed against estimated energy expenditure. The correlation coefficient (r) is 0.913, so [R.sup.2] = 83.3% of the variation in measured energy expenditure in the sample is explained by the model.

[FIGURE 1 OMITTED]

A second model, which contained no measure of fitness, was also fitted. The final prediction equation for energy expenditure using age, gender, weight and heart rate was:

EE = gender x (-55.0969 + 0.6309 x heart rate + 0.1988 x weight + 0.2017 x age) + (1 - gender) x (-20.4022 + 0.4472 x heartrate - 0.1263 x weight + 0.074 x age)

where gender = 1 for males and 0 for females. Table V shows the above model in a different format. The likelihood ratio test for goodness-of-fit [chi square] = 360.68 on five degrees of freedom with P < 0.0001. The results of type III tests for the fixed effects in the mixed model are given in Table VI. The degrees of freedom for the F-tests were calculated using Satterthwaite's method.

In Figure 2, the measured energy expenditure is regressed against estimated energy expenditure. The coefficient of correlation 0.857, so [R.sup.2] = 73.4% of the variation in measured energy expenditure in the sample is explained by the model.

[FIGURE 2 OMITTED]

Independent sample analysis for inner validation

Data from an independent sample of 17 participants (8 females, 9 males) were used to validate both models. Predicted energy expenditure using the first model, which included a measure of fitness (V[O.sub.2max]), correlated with measured energy expenditure during self-selected cardiovascular fitness training ($r = 0.836$, $P < 0.0001$; Figure 3). Using the second model for measuring energy expenditure, with no measure of fitness, the correlation coefficient was 0.77 ($P < 0.0001$) (Figure 4).

[FIGURE 3-4 OMITTED]

Agreement

Because we used a mixed model (with random participant effects), we had to use maximum likelihood estimation instead of least squares. The result is that even the estimates for the initial sample which was used to develop the equations are slightly biased. The bias of the estimates and their random variation for the four sets of estimates are summarized in Table VII. The bias is the difference between the predicted and the corresponding actual value of energy expenditure, and the 95% limits of absolute agreement were calculated as described in Atkinson and Nevill (1998). It is interesting to note that the bias in the initial sample is on average in the opposite direction to that for the validation sample. The fact that the agreement limits become wider down the table is completely logical. We believe that these limits are narrow enough for the underlying models to be of practical use.

Discussion

In this study, we demonstrated that physical activity energy expenditure during moderate- to high-intensity exercise may be predicted with good accuracy in a group of individuals varying widely in age, fitness and morphology, without the need for individual calibration. This study denotes an improvement over existing studies in the estimation of physical activity energy expenditure using heart rate monitoring. The proposed model (using heart rate, age, weight, gender and level of fitness V[O.sub.2max])) accounted for 70% of the variation in observed energy expenditure in an independent sample of people completing a self-selected 20-min cardiovascular exercise session.

Previous studies (Li et al., 1993; Rutgers, Klijn, & Deurenberg, 1997) have cited poor agreement between energy expenditure estimated using heart rate monitoring and measured energy expenditure. These prediction equations were developed on small samples, not representative of the population to which the equation was to be applied. Rutgers et al. (1997) developed a prediction equation based on the heart rate and energy expenditure data acquired from 13 elderly individuals. The authors concluded that the use of heart rate monitoring to measure energy expenditure was inaccurate over 3 days of measurement, citing large discrepancies between energy expenditure estimation using the individual calibration curve and a group curve. Li et al. (1993) also reported poor agreement for the estimation of energy expenditure using heart rate monitoring between group and individually derived estimates. Once again, this sample was relatively small, consisting of only 40 persons.

The current study represents an improvement over existing studies (Hiilloskorpi et al., 1999; Rennie et al., 2001) that used heart rate monitoring to estimate physical activity energy expenditure, without individual calibration. Previously, Rennie et al. (2001) used the variables that significantly interacted with energy expenditure to predict the slope, intercept and the heart rate flex point for measured versus predicted physical activity energy expenditure. In that study, the variables of sitting heart rate, age, weight and gender were found to have a significant impact on the slope, intercept and heart rate flex point. These investigators were then able to use the slope and intercept of the linear model to place 98% of the participants in their sample in either the same or adjacent quartiles for the measured and estimated physical activity levels. Their model has implications for physical activity classification in epidemiological models. In the current study, we derived linear equations, based on mixed-model analyses. These equations yield predictions that correlate significantly with the test sample as well as the independent validation sample.

Previously, Hiilloskorpi et al. (1999) developed an equation to predict energy expenditure using the variables of heart rate, age, weight and gender. They showed that the mode of exercise, cycling versus running, did not significantly affect the final prediction of energy expenditure. We also found that the mode of exercise did not affect the estimation of energy expenditure, and therefore suggest that the proposed equation may be used for both running and cycling activities. During our inner validation study, we even found good agreement with other models of continuous activity, such as stationary rowing ergometry and stationary stair-climbing activities.

Hiilloskorpi et al. (1999) did not include any measure of physical fitness or V[O.sub.2max] in their prediction equation, citing a need to produce an equation for estimating energy expenditure independent of laboratory testing. We found that when a measure of the level of cardiorespiratory fitness such as V[O.sub.2max] is included, the accuracy of the prediction improved. The correlation coefficients (r) of the study sample were 0.913 for the model V[O.sub.2max] with and 0.857 for the model without V[O.sub.2max]. The increase in variation explained by the model including V[O.sub.2max] is 83.4%-

73.4% = 10%. The correlation coefficients of the validation sample were 0.836 for the model with V[O.sub.2max] and 0.77 for the model without V[O.sub.2max]. The increase in variation explained by the model including V[O.sub.2max] is approximately 10%. It is well known that training results in adaptations in the heart rate response to increasing workloads (Meijer, Westerterp, & Verstappen, 1999; Wilmore et al., 1996). Therefore, it is not surprising that an indirect measure of cardiorespiratory fitness improves the accuracy of the prediction of energy expenditure from heart rate. This finding is in line with the study of Rennie et al. (2001), in which sitting heart rate was found to play a significant role in the prediction of energy expenditure from heart rate monitoring. Rennie et al. (2001) proposed that resting heart rate when sitting was a useful proxy measurement for fitness, since previous studies have found an inverse association between resting tachycardia and maximal exercise capacity (Blair, Kannel, Kohl, Goodyear, & Wilson, 1989), as well as a positive relationship between regular participation in physical activity and lower resting heart rate, independent of age (Steinhaus et al., 1988).

Hiilloskorpi et al. (1999) found that including age in the regression model did not significantly improve the variance. This is at odds with the current study, as we found that age did contribute significantly to the final mixed model. This difference may partly be explained by differences in sample characteristics. Hiilloskorpi et al. (1999) acknowledges a relatively narrow age range, with few participants older than 50 years or younger than 25 years. In our study, the mean age of the 72 men was 31 years (range 19-50 years) and that of the 43 women was 30 years (range 22-44 years). In the study of Hiilloskorpi et al. (1999), the mean age of the 45 men was 40 years and that of the 43 women was 38 years. Their participants were notably older than those in the current study. In addition to the age discrepancies between the two studies, there were also discrepancies between the fitness of the two samples. In the current study, the mean V[O.sub.2max] for the men was 59.2 ml x [min.sup.-1] x [kg.sup.-1] and for the women it was 45.7 59.2 ml x [min.sup.-1] x [kg.sup.-1]; in the study of Hiilloskorpi et al. (1999), the mean values were 48.5 and 39.5 ml x [min.sup.-1] x [kg.sup.-1] for the men and women respectively. These demographic differences may partly account for the differences found between the two prediction models. Rennie et al. (2001) also found that age impacted in the regression model of physical activity energy expenditure from heart rate. It may be argued that the sample used to generate the prediction equation comprised a well-trained group of individuals, but we feel that they represented a typical fitness centre population. Maximal oxygen uptake ranged from 27.0 to 64.1 ml x [min.sup.-1] x [kg.sup.-1] in the women and from 38.0 to 81.4 ml x [min.sup.-1] x [kg.sup.-1] in the men. It was the intention of the present study to apply this equation to the general exercising population and, as a result, our recruitment focused on a local fitness centre, amateur running clubs and cycling races. While our average fitness levels were unlike those presented in both Hiilloskorpi et al. (1999) and Rennie et al. (2001), we have demonstrated that the inclusion of V[O.sub.2max], as a proxy for fitness, improves the predictability of our group-based equation.

While many other studies (Hiilloskorpi et al., 1999; Li et al., 1993; Rennie et al., 2001; Strath et al., 2000) have used similar approaches to develop prediction equations without individual calibration, not all of them (Hiilloskorpi et al., 1999; Strath et al., 2000) used an independent sample for inner validation of the developed model and, in some cases, did not report inner validation of the developed model (Strath et al., 2000) or used the same sample for which the original prediction equation was developed (Hiilloskorpi et al., 1999). This may lead to elevated levels of agreement between the prediction models and measured estimates, due to the homogeneous nature of samples. For example, Strath et al. (2000) estimated physical activity during moderate-intensity exercise using heart rate monitoring and reported good agreement ($r = 0.87$) between measured and estimated energy expenditure; however, in this study, no inner validation was performed on an independent sample of participants. Conversely, Rennie et al. (2001) validated a prediction equation for physical activity levels, developed on a sample of 789 individuals, on a smaller subset of 97 individuals. During this inner validation, 98% of the subset was placed in the same or adjacent quartiles during comparison of measured and estimated physical activity levels. In the current study, we found good agreement on an independent sample of participants. The prediction equation explained 71% of the variance in estimated energy expenditure in an independent sample, during self-selected cardiovascular exercise training.

Finally, for practical application the proposed equations represent an improvement in the estimation of energy expenditure from heart rate over existing equations. They may be used in large population-based studies for health purposes. Further research is needed on the simultaneous measurement of physical activity energy expenditure and heart rate. Predictive equations that estimate energy expenditure for health research and promotion are required for a wider variety of activities, particularly for intermittent activity or activity conducted at lower intensities.

Table I. Characteristics of the sample used to develop the prediction equation (mean [+ or -] s)

	Treadmill	
	Men (n = 22)	Women (n = 24)
Age (years)	30 [+ or -] 7	30 [+ or -] 6
Weight (kg) *	76 [+ or -] 10	66 [+ or -] 11
Percent body fat *	14.5 [+ or -] 4.8	26.8 [+ or -] 5.2
V[O.sub.2max] (ml x		

[kg.sup.-1] x [min.sup.-1]) *	65.0 [+ or -] 8.6	49.0 [+ or -] 9.7
Maximal heart rate (beats x [min.sup.-1])	189 [+ or -] 9	184 [+ or -] 9
Cycle ergometer		
	Men (n = 50)	Women (n = 19)
Age (years)	31 [+ or -] 6	31 [+ or -] 6
Weight (kg) *	81 [+ or -] 13	62 [+ or -] 6
Percent body fat *	16.6 [+ or -] 4.2	23.1 [+ or -] 5.0
V[O.sub.2max] (ml x [kg.sup.-1] x [min.sup.-1]) *	55.3 [+ or -] 8.3	48.3 [+ or -] 8.1
Maximal heart rate (beats x [min.sup.-1])	187 [+ or -] 11	185 [+ or -] 9

* P < 0.00001, differences between the sexes.

Table II. Characteristics of the sample used for inner validation (mean [+ or -] s)

	Men (n = 9)	Women (n = 8)
Age (years)	29 [+ or -] 8	34 [+ or -] 10
Weight (kg) *	81 [+ or -] 14	62 [+ or -] 9
Percent body fat *	14.8 [+ or -] 5.1	26.0 [+ or -] 3.9
V[O.sub.2max] (ml x [kg.sup.-1]		

x [min.sup.-1]) *	54.3 [+ or -] 11.4	42.4 [+ or -] 5.4
Maximal heart rate (beats x [min.sup.-1])	190 [+ or -] 9	178 [+ or -] 15

* P < 0.00001, differences between the sexes.

Table III. The estimates and their standard errors for the fixed effects of the model including fitness

	Men		Women	
Effect	Estimate	Standard error	Estimate	Standard error
Intercept	-95.7735	9.5734	-59.3954	17.1314
Heart rate	0.6344	0.0137	0.4498	0.0165
Weight	0.3942	0.0642	0.1032	0.1166
V[O.sup.2max]	0.4044	0.0837	0.3802	0.1575
Age	0.2713	0.1120	0.2735	0.2087

Table IV. Table with type III analysis for fixed effects of model including fitness

Effect	Degrees of freedom	F-value	P-value
Gender	2, 109	56.05	< 0.0001
Heart rate x gender	2, 125	1444.98	< 0.0001
Weight x gender	2, 100	19.23	< 0.0001
V[O.sub.2max] x gender	2, 101	14.57	< 0.0001
Age x gender	2, 101	3.79	0.0258

Table V. The estimates and their standard errors for the fixed effects of the mixed model without fitness

Effect	Men Estimate	Men Standard error	Women Estimate	Women Standard error
Intercept	-55.0969	5.5780	-20.4022	7.2318
Heart rate	0.6309	0.0137	0.4472	0.0165
Weight	0.1988	0.0619	-0.1263	0.1061
Age	0.2017	0.1180	0.0740	0.1742

Table VI. Results of type III tests for fixed effects of model excluding fitness.

Effect	Degrees of freedom	F-value	P-value
Gender	2, 109	14.43	0.0002
Heart rate x gender	2, 125	1428.63	< 0.0001
Weight x gender	2, 99.9	5.86	0.0039
Age x gender	2, 100	1.55	0.2170

Table VII. Summary of the bias of the energy expenditure (in kJ x [min.sup.-1]) estimates and their random variation for the four sets of estimates

Sample	Model	Mean	Standard deviation
Initial	Including fitness	-1.06	7.83
Initial	No fitness	-5.79	9.85
Validation	Including fitness	8.19	9.19
Validation	No fitness	6.27	9.65

Sample	95% limits of agreement	
Initial	-16.41	14.28

Initial	-25.10	13.52
Validation	-9.83	26.21
Validation	-12.65	25.19

Note: The bias is the difference between the predicted and the corresponding actual value of energy expenditure.

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