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A stepwise science-industry collaboration to optimize the calculation of energy expenditure during walking and running with a consumer-based activity device

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ABSTRACT

Physical activity (PA) and sedentary behavior (SB) have important implications for health benefits. A growing number of people use consumer available wearables such as activity trackers, which claim to objectively monitor PA and SB in free-living conditions. These devices could provide essential information to understand the influence of behavior on health. This understanding assumes that available consumer products correctly monitor PA in the everyday life. A general approach in science is to validate such activity devices in a controlled environment. The classical procedure to investigate criterion validity is to examine new devices based on the gold standard. To our knowledge, the resulting validation data are not often analyzed and shared with manufacturers to further develop and improve the activity device. The current study can be seen as a validation study to check the criterion validity of a consumer-level activity device. The novelty of this study was the application of a stepwise approach to optimize the calculations of a consumer available activity device (i.e., Activ8; www.activ8all.com/product/activ8-professional-activity-monitor/) for estimating energy expenditure (EE) in walking and running.

Forty adults (27 males and 13 females) participated in three substudies. Each substudy consisted of several walking and running activities in which EE was simultaneously measured with indirect calorimetry (as reference value) and the Activ8 activity device. EE values at each walking and running speed were compared to identify the accuracy of the Activ8 device. After completion of the first and second substudies, the results were shared and discussed with the manufacturer of Activ8. Next, the calculations for EE were adapted to the indirect calorimetry values to improve accuracy. In the second and third substudies, the modifications were tested, and results were used to further optimize the calculation of EE.

The results of this study show an improved correlation between EE measured by indirect calorimetry and the Activ8 activity device (R2 from 0.91 to 0.95); a decrease in differences between substudy A and substudy B considering EE measured (indirect calorimetry) and calculated (Activ8 calculation) was observed. The second modification in the calculation showed a further increase in correlation (R2 from 0.95 to 0.97) between the measured and calculated EE; however, the absolute difference between the two values increased. The results from a validation study are valuable to use for further adaptation of accelerometer device calculations. A stepwise science-industry collaboration can improve the calculation accuracy and may be a practical approach for validation studies in which human movement scientists and technology manufacturers work together to successfully improve the validity and accuracy of consumer-based activity devices.

1. Introduction

Physical activity (PA) has important implications on health benefits [1–4]. For example, a longitudinal study in which 12,000 older men were followed for 10–13 years showed that sustained PA is associated with improved survival and health [5]. Due to technical developments, quantification of movement with accelerometers has become a predominant study topic to describe PA [6] and will be in sedentary behavior (SB) [7]. Additionally, the consumer market for these wearables has grown exponentially in recent years [8,9]. Given the necessity for regular PA [10] and interrupting sedentary time [11,12] in maintaining health [13], valid methodologies must be developed to measure PA and SB under the unconfined conditions of daily life [14–16]. Accurately monitoring and objectively assessing PA and SB is necessary for the quantification of health benefits.

Historically, early piezoresistive accelerometers that were able to capture static acceleration, such as the gravitational field, were hampered by a large battery unit and limited battery life [17,18]. Many motion sensors, therefore, switched from piezoresistive to piezoelectric accelerometers, which required less battery power, were considerably smaller in size and allowed data capture over longer periods of time, often up to 3 weeks [17,19,20]. Additionally, accelerometers became more sophisticated, and multiple axes were integrated into smaller devices with improved battery life [18]. As a result, devices could be worn not only on the lower back (close to the body center gravity point) but also on other parts of the body such as the hip, waist, ankle, chest,

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upper arm, thighs, wrist and foot [21]. These wear location variations made it possible to distinguish between PA and SB [14].

Today, accelerometer-based activity devices can provide information on the total amount, intensity, duration and frequency and type of physical activities performed [22].

Accelerometer movement is a direct result of body movement (physical activity); thus, accelerometer data can be used to calculate energy expenditure (EE); and any bodily movement produced by skeletal muscles results in an increase in EE [23]. However, a single regression equation for calculating EE does not work across a wide range of activities [24]. Calculating EE from accelerometer data is a suitable approach that is possible in 3 ways [25]: (a) count-based estimation methods, (b) activity-specific estimation methods using a chart with the metabolic equivalent of task (MET), and (c) activity-specific estimation methods using the accelerometer features. Altini et al. [25] state that activity-specific estimation methods are considered to perform better than the other two accelerometer methods.

Researchers are typically interested in the accuracy of quantifying physical (in)activity [26], while customer end-users prefer understandable information about a PA for self-monitoring and goal setting [27]. Compared to consumer-based devices ($40-$250) [28], research-based electronic activity monitors are more expensive ($400-$4000, depending on the brand and measurement complexity) [29]. Moreover, the increased availability of wearable technology provides consumers with various options of self-care [30]. This situation is in line with a more general trend of people becoming 'experts' in self-monitoring of health parameters and physical activity, often referred to as quantified self [31,32]. Unlike research-based devices that can provide a researcher with raw data [29], consumer-based devices provide information selected by the manufacturer [28]. This consumer market of wearables devices, especially activity trackers, has grown enormously in the past few years, with activity and fitness trackers representing 85% of the market sales [33]. One in six (15%) [27] consumers in the United States currently uses wearable technology, including smartwatches or fitness bands, even though a recent commercial study found higher values (33%) [34]. These monitors do well in measuring sleep time and the amount of steps [35], but they do not often accurately estimate EE [35,36]. In most studies, the validity of an accelerometer is assessed by comparing the accelerometer data with other devices (cross-validation) [37] or with a so-called 'gold-standard' method (criterion validation) such as doubly labeled water [38]. This classical approach to validation, as applied by Kumahara et al. [39], is suitable to assess the accuracy levels and the extent of agreement between these devices; however, this method is not intended to optimize the accuracy of (new) devices. The latter is the first aim of this research, and it is hoped that the results contribute to improved accelerometer validation. Second, this research will explore the potential of a stepwise approach in which science and industry collaborate to optimize the calculations of an available consumer activity monitor for estimating energy expenditure (EE) while walking and running.

Activ8 (www.activ8all.com, 2 M Engineering, Valkenswaard) is both a consumer-based device and a hardcore research-based device. It is an affordable ($100) triaxial accelerometer that can be carried in a trouser pocket (easy to use) and recognizes movement time in several postures and six types of (physical) activity (i.e., lying, sitting, standing, walking, running and cycling). The Activ8 is, to our knowledge, the first consumer-based device that is worn on the thigh (good location for activity recognition [40] and intensity level [14]) and uses an activity-specific estimation of energy expenditure by means of an intensity factor, as suggested by Altini et al. [25]. These factors improve the use of this device over a wrist or hip device that are most commonly used in consumer-based activities [28].

Activ8 has an accuracy of 94% in recognizing various activities [41], based on its position coinciding with the gravity field and the 3-axis pattern of the accelerometer. The interface of Activ8 displays total seconds in each posture/activity per minute. Next, the device calculates an activity index for each minute per posture and activity based on accelerations (m/s2). The EE (kcal/min) value for each minute is calculated for each activity and posture. These calculations are based on the basal metabolic rate (BMR), time in activity and activity index. The original calculation for EE that was used in Activ8 was based on desk research. Information about average EE values at different walking [42] and running speeds [43] can be found in the literature, but individual values vary from the average values [44].

To the best of our knowledge, Activ8 calculations have not been compared to any other methods of measuring EE (e.g., indirect calorimetry). Therefore, there is no information on the calculation accuracy for EE. To investigate this accuracy, individual values of the accelerometer and indirect calorimetry data have to be compared.

Adaptation of the accelerometer calculations to simultaneously measure indirect calorimetry data in the same individual is preferable to optimize the calculation. The adapted calculations can be investigated in a new group of individuals to show the calculation strength. The new validation can provide information for a second calculation adaptation.

The optimization of the accuracy is the first aim of this research and the results might contribute to the state of the art regarding the validation of accelerometers. Secondly, research will explore the potential of a stepwise approach in which science and industry collaborate to optimize the calculations of a consumer available activity monitor for estimating energy expenditure (EE) for walking and running.

2. Method

2.1. Participants

Forty adults (27 males and 13 females), divided into 3 substudy groups, participated voluntarily in the study. Individuals were recruited from within the University by posted announcements and word of mouth. Subjects were eligible for inclusion if they could walk and run without walking aids, and their characteristics are presented in Table 1. The ethical base of the study is in line with the Helsinki declaration and was approved by the research board of Fontys School of Sport Studies. All subjects signed an informed consent before starting the study. The study design consisted of three consecutive studies with subsequent equation modifications to the Activ8 data.

2.2. Protocol

First, in substudy A, six subjects performed three walking activities at 2 km/h, 4 km/h and 6 km/h with 0% inclination and three running activities at 8 km/h, 11 km/h and 14 km/h with 1% inclination [45] on a treadmill (Lode Katana Sport, Groningen, Netherlands) for 5 min each with 15 s of standing between each activity to distinguish speed changes in the accelerometer data more accurately. These three walking and running speeds were chosen to limit the total test time for participants to 30 min. The chosen speeds were based on an earlier study in which the same range of speeds were used [46]. The Activ8 was worn on the thigh during protocol, and energy expenditure was measured using indirect calorimetry (Cortex Metalyzer 3b, Leipzig,

Table 1
Subject characteristics (Mean ± SD).

	Study A (n = 6)	Study B (n = 16)	Study C (n = 18)
Age (y)	24.2 ± 5.8	28.8 ± 11.1	22.7 ± 7.0
Weight (kg)	74.8 ± 11.8	67.6 ± 7.6	68.3 ± 9.1
Length (cm)	180.7 ± 7.7	174.9 ± 9.2	174.9 ± 8.6
BMI (kg)	22.9 ± 3.3	22.0 ± 1.4	22.3 ± 1.9
BMR (Harris and Benedict) (Kcal/day)	1803.2 ± 195.3	1649.0 ± 142.3	1683.0 ± 185.3

Germany). After data were collected, the calculation was optimized according to the measured energy expenditure by the manufacturer of the Activ8 device.

In substudy B, the new calculation was applied for 16 subjects with a slightly modified protocol to distinguish changes with smaller increases in walking and running speed. Subjects performed five walking activities at 3, 4, 5, 6 and 7 km/h with 0% inclination and six running activities at 8, 9, 10, 11, 12, 13 and 14 km/h with 1% inclination for 3 min each with 15 s rest (standing) between each step. Data were collected, and the calculation was adapted to the new measurements.

Eighteen subjects participated in the last part of the study (substudy C) to investigate the calculation accuracy for energy expenditure. The protocol in substudy C was the same as that in substudy B.

2.3. Measurements

Continuous indirect calorimetry was used as a reference for energy expenditure (Cortex Metalyzer 3b, Leipzig, Germany). Oxygen (VO_2 in L/min) and carbon dioxide (VCO_2 in L/min) were measured breath by breath, and the average values of the last minute in each step were used to calculate energy expenditure (kcal/min) according to Weir's formula [47].

The Activ8 EE (kcal/min) for each minute of walking and running was calculated for each subject. These calculations are based on BMR [48], time in activity and calculated activity index (based on accelerations).

Simultaneously, raw x, y, z acceleration data (ranging −2 G to 2 G) from all activities were recorded by the Activ8 with a frequency of 12.5 Hz. Raw data and EE data from indirect calorimetry were used to improve the calculation according to the calorimetric data.

2.4. Statistical analysis

A statistical analysis was performed with SPSS V22.0 (SPPS Inc., Chicago, Illinois, Unites States). Correlations between the two measurements (accelerometer and indirect calorimetry) were calculated. A two-way repeated measures ANOVA (running speed and measuring method as factors) was performed for each of the three studies to investigate differences in EE between the indirect calorimetry and accelerometer data. P-values < 0.05 were considered as statistically significant.

3. Results

The results from substudy A (see Fig. 1) revealed that the estimated EE by the Activ8 is largely in line with that determined by indirect calorimetry. The total dataset showed a correlation of 0.91 between the calculated (Activ8) and measured (indirect calorimetry) EE. Repeated measures of ANOVA showed differences between the indirect calorimetry and Activ8 values ($p = 0.048$), and the post hoc analysis showed that this difference was at the two highest running speeds (11 ($p = 0.015$) and 14 km/h ($p = 0.010$)).

In substudy B, the correlation of the total dataset was 0.95 between the calculated (Activ8) and measured (indirect calorimetry) EE (see Fig. 2).

Repeated measures of ANOVA showed a difference between the indirect calorimetry and Activ8 values ($p = 0.019$). A post hoc test showed a significant difference at 5 ($p = 0.010$) and 9–11 km/h ($p < 0.016$).

In substudy C, a total correlation of 0.97 was found (see Fig. 3). However, repeated measures of ANOVA, showed a significant difference between the indirect calorimetry and Activ8 values ($p = 0.000$). A post hoc test showed a significant difference at all walking and running speeds ($p < 0.01$).

Two Bland-Altman plots for walking (Fig. 4) and running (Fig. 5) are presented to visualize the correlation and agreement between the two methods [49]. Data from substudy B are presented because these data showed a high correlation and fair to high agreement between the two methods. In these study data, all subjects showed an increase in underestimation of the Activ8 EE compared to that for calorimetry EE with increasing speeds.

4. Discussion

The results of this study show an improvement in agreement and decrease in difference between substudy A and substudy B with the measured (indirect calorimetry) and calculated (Activ8 calculation) EE values. This result suggests an improvement in the prediction of the activity monitor calculation after the first change. The second change in calculation showed an increase in agreement between measured and calculated EE; however, the difference between the two values increased. This finding can be explained by a better indication of the intensity differences of the different speeds but a less accurate calculation of EE at each intensity in the first adapted calculation. All calculated EEs overestimated the measured energy expenditure by a similar degree.

The first calculation adaptation can be seen as the 'optimal' calculation in this study. The aim of this study was to apply a stepwise approach to optimize the calculation of EE during walking and running with a consumer-based activity monitor. To the best of our knowledge, this is the first study that uses a stepwise approach to improve the EE calculation from consumer-available accelerometer data. The classical procedure to investigate the validity is to measure the new devices with the gold standard. We used indirect calorimetry as the reference for EE during walking and running activities; however, these data were also used to optimize the Activ8 calculation of EE. The results of this study show that collaboration between movement scientists for providing the EE data and technicians for adapting the calculation based on measured EE and measured accelerometer data. This is a promising approach to integrate validation with product improvement.

The accuracy of a consumer activity monitoring device is important, but usability and unobtrusiveness are equally as important. For instance, the accuracy of activity recognition is better with multiple location accelerometer data [50], but for the consumer based market, the use of multisensors can place a burden on the users, and compliance will be low. For the consumer-based market, the use of multisensors can be a burden on the users, causing compliance to be low. Wearing an activity monitor in a trouser pocket can help the monitor to distinguish several activities and can therefore be a great benefit for consumers because of the ease of use during such activities.

This study was performed in a laboratory setting on a treadmill (i.e., focusing on efficacy) and not in a real environment (effectiveness); therefore, differences may occur in EE results between a treadmill and walking or running in a field [51]. In 1996, Jones and Doust [45] demonstrated equality of the energetic cost of a treadmill and outdoor running with the use of a 1% treadmill grade; therefore, this study used this 1% inclination. Moreover, McMiken et al. [52] noted that submaximal exercise on the track and treadmill elicited the same physiological responses when running at low to moderate speeds. Although, Pugh [53,54] reported that running at speeds above 4.0 m/s (14.4 km/h) can result in an increase in EE up to 16% because of the energy cost of overcoming wind resistance. Jones and Doust [45] suggested that this greater increase in EE is at 5.0 m/s (18 km/h). Both speeds (4.0 and 5.0 m/s) are above the maximal running speed in the current study; therefore, we can assume that this increase in EE did not negatively influence the study results.

Recently, it has been suggested that breath-by-breath metabolic gas exchange systems may fail in accuracy because of inaccurate ventilation and metabolic rate measurements in the lower ventilation range [55].

However, Huszczuk and Haouzi [55] conclude that these lower ventilation ranges can only be expected in pediatric COPD and cardiac patients. Our subjects performed exercise intensities from walking to

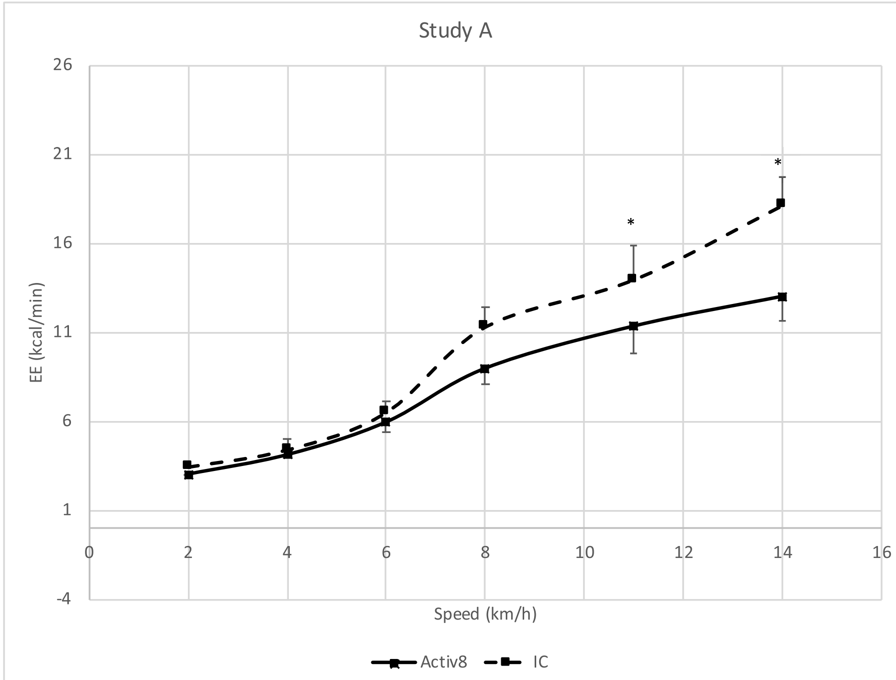

Fig. 1. Sub-study A Activ8 vs indirect calorimetry (IC) energy expenditure (kcal/min) during walking and running. Values represent mean ± SD; *p < 0.05.

running, so ventilation is sufficiently high to be in the appropriate range. All together, we are confident that the indirect calorimetry measurements in the laboratory setting can be extrapolated to EE values in a real environment and can be used as reference values for Activ8 calculations.

Criterion validity similar to that in the current study, along with other types of validation and reliability in PA and SB, were discussed by Kelly et al. [26]. The authors argue that the lack of consensus about addressing concepts of validity and reliability led to inconsistencies and, as a result, confusion within the field of physical activity and sedentary behavior. The current study can be seen as a validation study to verify the criterion validity of an activity device. By definition, such a study investigates the extent of agreement between two measures, from which one is the gold standard. This study partly reflects such a validation study, but we took it a step further. Data from the first 'validation' study were used to change the calculation of the activity monitor to increase the constructed validity. This information was checked in the second substudy. After this, the first adaptation could be satisfied with the result, but we investigated whether a second adaptation would further increase the agreement. Accurately measured energy expenditure data were used not only for comparison with the calculated energy expenditure with an accelerometer but also for improving the calculation accuracy. This stepwise approach is intended to adapt the calculation step-by-step until the adaptation does not lead to a further increase in agreement. At this point, further calculation improvement is not possible. Therefore, we are more certain that the calculation considered to be the best could not be further be improved within the current device. Designers and engineers who develop these

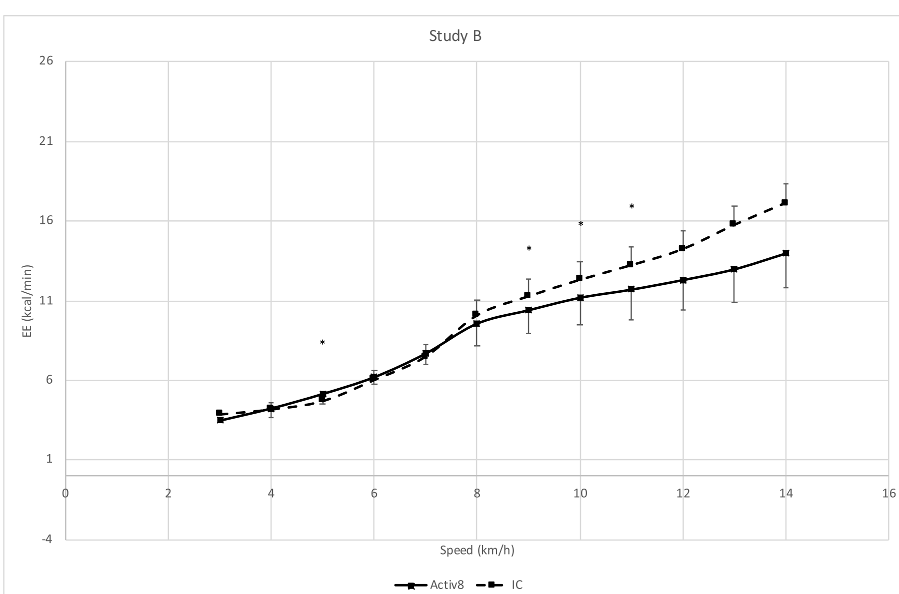

Fig. 2. Sub-study B Activ8 vs indirect calorimetry (IC) energy expenditure (kcal/min) during walking and running. Values represent mean ± SD; *p < 0.05.

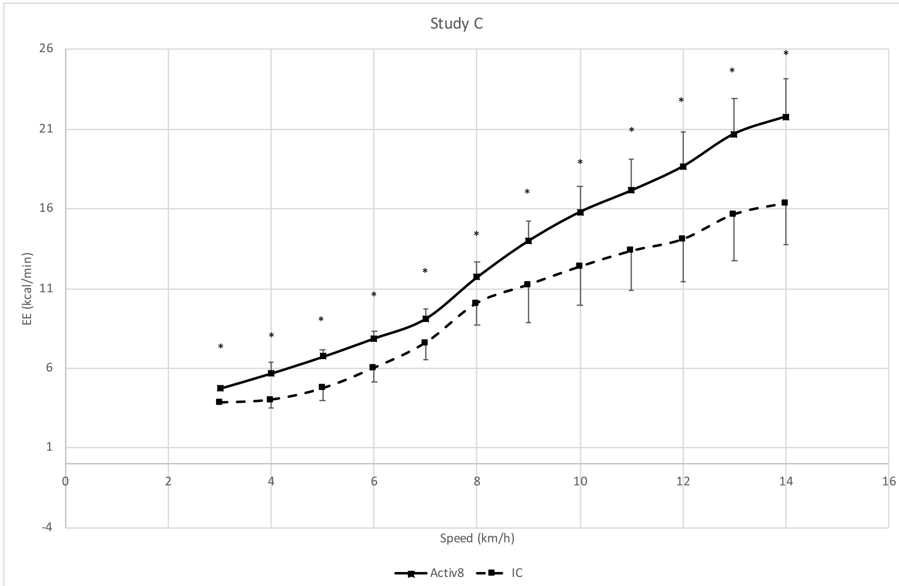

Fig. 3. Sub-study C Activ8 vs indirect calorimetry (IC) energy expenditure (kcal/min) during walking and running. Values represent mean ± SD; *p < 0.05.

devices can use and require the input of accurately measured data to improve the validity of the device. Therefore, cooperation between human movement scientists, designers and engineers as a multi-disciplinary team can improve accuracy of the device in a shorter amount of time.

5. Conclusion

The second calculation of Activ8 predicted energy expenditure fairly well in a laboratory setting. A stepwise approach to improve the accuracy of the calculation is a practical approach for validation studies in which science and industry combine knowledge to quickly improve the validity of a consumer-based accelerometer. However, future research will have to demonstrate the accuracy of the Activ8 in real-life validation studies.

Acknowledgements

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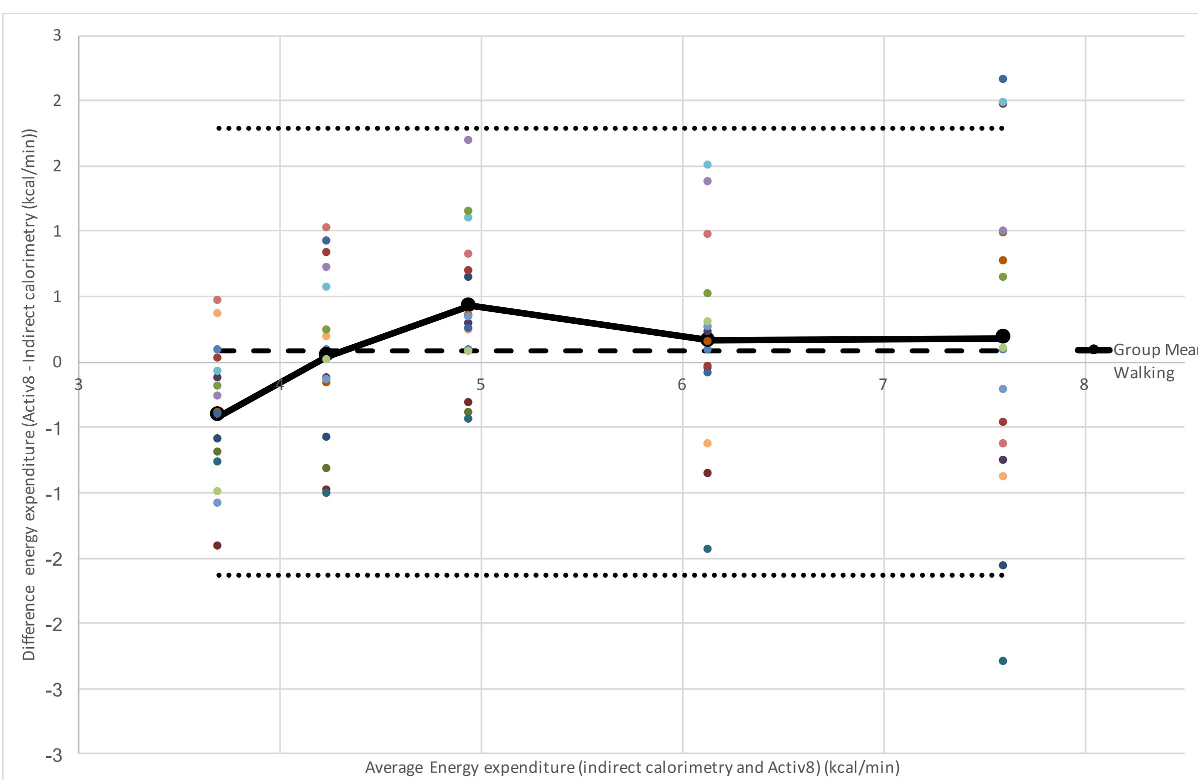

Fig. 4. Bland-Altman plot indirect calorimetry (IC) and Activ8 Energy Expenditure for walking of sub-study B (N = 16).

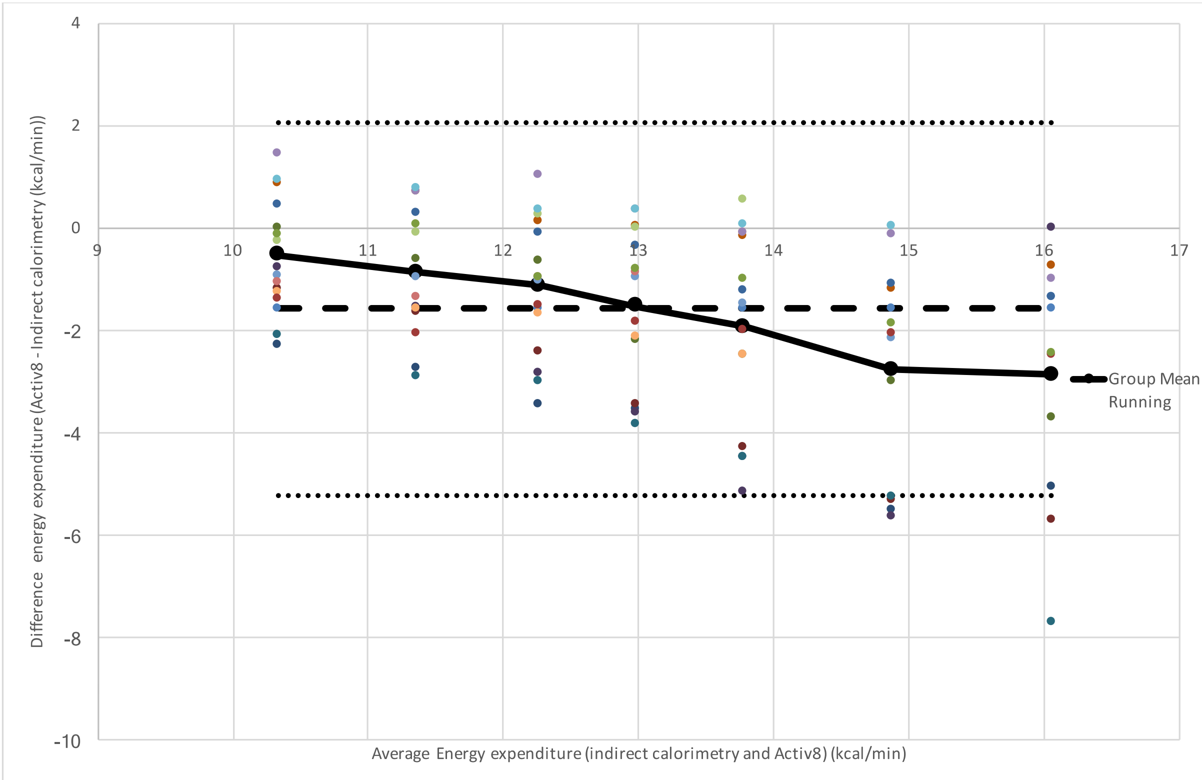

Fig. 5. Bland-Altman plot Indirect calorimetry and Activ8 Energy Expenditure for running of study B (N = 16).

Appendix A. Supplementary data

Supplementary data related to this article can be found at https://doi.org/10.1016/j.techsoc.2018.09.001.

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