Classification of physical activity cut-points and the estimation of energy expenditure during walking using the GT3X+ accelerometer in overweight and obese adults

Abstract

This study establishes tri-axial activity count (AC) cut-points for the GT3X+ accelerometer to classify physical activity intensity in overweight and obese adults. Further, we examined the accuracy of established and novel energy expenditure (EE) prediction equations based on AC and other metrics. *Part 1:* Twenty overweight or obese adults completed a 30 minute incremental treadmill walking protocol. Heart rate (HR), EE and AC were measured using the GT3X+ accelerometer. *Part 2:* Ten overweight and obese adults conducted a self-paced external walk during which EE, AC and HR were measured. Established equations (Freedson, 1998; Freedson VM3, 2011) overestimated EE by 40% and 31%, respectively ($p < 0.01$). Novel gender-specific prediction equations provided good estimates of EE during treadmill and outdoor walking (standard error of the estimate = 0.91 and 0.65, respectively). We propose new cut-points and prediction equations to estimate EE using the GT3X+ tri-axial accelerometer in overweight and obese adults.

KEYWORDS**:** accelerometry; ambulatory monitoring; MVPA, prediction equations

Background

Walking is an accessible low-impact form of physical activity (PA) that can contribute to the attainment of the recommended 150 minutes (min) of moderate intensity PA per week (U.S. Department of Health & Human Services, 2008). Walking is a simple yet effective way to increase energy expenditure (EE) and therefore is a prime focus of weight loss intervention research (Richardson et al., 2008), especially in overweight and obese populations, where participation in other forms of PA is problematic. Evidently, a precise and objective measurement of EE and time spent engaging in PA would be beneficial in walking-based intervention studies where the assessment of energy balance in overweight and obese individuals is critical.

Accelerometers are a practical method of assessing objective PA in free-living populations by recording bodily movements reported as activity counts (AC) in either uni- or tri-axial planes of motion (Dellava & Hoffman, 2009), and less expensive and restrictive than methods such as doubly-labelled water, direct and indirect calorimetry. The AC generated by accelerometers allow researchers to develop usable and activity specific cut-points under controlled conditions, that allow for the objective assessment of time spent in light, moderate, vigorous PA (Colley & Tremblay, 2011). A plethora of previous research has now established cut-points in children and healthy, mixed cohort adults (Heil, 2006; Pfeiffer, Mciver, Dowda, Almeida, & Pate, 2006; Sasaki, John, & Freedson, 2011; Welk, Schaben, & Morrow, 2004).

In addition to the generation of specific cut-points the AC reported by accelerometers can be used in combination with body mass (BM) to generate multiple-regression derived estimates of EE (Crouter, Clowers & Bassett, 2006; Godfrey, Conway, Meagher & ÓLaighin 2008; Johannsen et al., 2010). One of the most widely used models of tri-axial accelerometers in

research studies is the GT3X+ (ActiGraph, LLC, Fort Walton Beach, FL), which was utilised in the large scale National Health and Nutritional Examination Survey (NHANES) in the U.S. (Hawkins et al., 2009). For accelerometer derived estimates of EE the GT3X+ software gives users the option of employing, amongst others, the Freedson (1998) equation (Freedson, Melanson & Sirard, 1998) based on AC from the vertical axis or the Freedson vector magnitude (2011) (VM3) equation (Sasaki et al., 2011) which utilises AC from all three axes of motion. These equations are commonly employed to assess PA and EE in research studies. Both equations were developed using male and female participants who were either within the healthy BMI range (Freedson et al., 1998) or a mixture of healthy weight and overweight participants (Sasaki et al., 2011). However, some research suggests that both equations have poor agreement with measured EE during walking exercise in adults (Lyden, Kozey, Staudemeyer & Freedson, 2011; McMinn, Acharya, Rowe, Gray & Allan, 2013). One possible explanation for this is that the equations fail to distinguish between differences in body composition between males and females. Furthermore, existing software algorithms are based on data collected from predominantly lean participants, yet obese individuals have been shown to be less efficient during normal walking speeds with significant individual variation in efficiency when age, gender and fitness level are taken into account (Chen, Acra, Donahue, Sun & Buchowski, 2004). Additionally cut-points generated from generic anthropometric variables such as BMI can lead to potential bias, as the effects of BMI seem greater for ambulatory activities, therefore highlighting the need for specific cut-points for various demographic subgroups (Watson, Carlson, Carroll & Fulton, 2014). To our knowledge there are no specific PA cut-points or EE prediction algorithms for the GT3X+ accelerometer that are specific for overweight and obese adults.

Incorporating a physiological parameter such as heart rate (HR) into the algorithm in combination with AC and BM may also enhance the predictive accuracy of accelerometers. Previous research indicates that combining AC and HR provides a more accurate prediction of EE when compared to either measure alone (Haskell, Yee, Evans & Irby, 1993; Luke, Maki, Barkley, Cooper & McGee, 1997; Crouter, Churilla & Bassett 2007; Fudge et al., 2007). The latest model of the GT3X+ (the wGT3X+) allows concurrent measurement of AC and HR and therefore offers intriguing potential as a practical and valid method to assess free-living EE.

Therefore, the primary purpose of this study was to a) develop tri-axial AC cut-points for the GT3x+ accelerometer to classify PA intensity in overweight and obese adults; and b) develop gender- and population-specific EE prediction equations using combinations of AC, HR and BM and to assess their accuracy at predicting EE during structured walking on a treadmill and self-paced walking in the field in overweight and obese adults. A further objective of this study was to examine the accuracy of established and commonly used prediction equations for estimating EE during walking exercise in overweight and obese individuals.

Methods

Participants and Design

Two separate cohorts of overweight or obese, but otherwise healthy participants were recruited directly from local weight management programs, as well as poster and Internet advertisements. Separate cohorts were utilised to enable a robust validation of novel prediction equations in a separate cohort to that of which the equations were generated. All participants provided written informed consent to participate in a study that was approved by the Faculty of Science, Engineering and Computing Ethics Committee (Kingston University London, UK), and all participants had the opportunity to receive feedback detailing their

results. Inclusion criteria for participation required that participants exhibited at least two of the following: BMI >25 kg/m^2; a waist to hip ratio of >1.0 for males and >0.85 for females; and a waist circumference >80 cm for females and >94 cm for males. All procedures were conducted in accordance with the Declaration of Helsinki.

Participants in each of the two parts of the study were required to report to the Exercise Physiology Laboratory at Kingston University, London on one occasion after being asked to refrain from alcohol and any strenuous exercise for the previous 24 hours and food or caffeine 3 hours prior to testing. Upon arrival, participants' anthropometrics were measured; stature, using a floor stadiometer (Holtain Ltd., Dyfed, Wales) and BM using electronic scales (Seca, Vogel & Halke, Germany). Hip circumference and waist circumference were also measured according to the International Standards for Anthropometric Assessment using a tape measure (Bodycare Products Ltd, UK) and waist to hip ratio was calculated by dividing waist circumference by hip circumference.

Part 1

Twenty overweight and obese adults (12 females and 8 males) were recruited (mean ± SD; age 43 ± 11 years, stature 171 ± 10 cm, BM 89.6 ± 19.7 kg, BMI 30.5 ± 4.9 kg/m^2, waist circumference 98 ± 14 cm, waist to hip ratio 0.87 ± 0.08). The test protocol consisted of continuous walking on a treadmill (H/P/Cosmos Venus, Germany); made up of five incremental stages lasting 5 min each. The initial speed was set to 4 km·h^{-1} and increased by 0.5 km·h^{-1} every 5 min until the participants felt they were about to break into an involuntary jog/run or they felt like they could not continue. The speeds selected were based on the range of walking speeds used in previous accelerometer validation studies (Freedson et al., 1998; Sasaki et al., 2011). The walking speed of 6.5 km·h^{-1} was excluded from the data analysis as the majority of participants were unable to complete this stage. Throughout the test, breath-

by-breath pulmonary gas exchange was measured via indirect calorimetry (Oxycon Pro, Carefusion, UK) which was calibrated prior to each test as per the manufacturer's guidelines. EE was calculated using the Weir equation (Weir, 1949) as follows: EE $(kcal \cdot min^{-1}) = (VO_2 \times 3.941) + (VCO_2 \times 1.1)$. Whereby VO_2 is the rate of oxygen consumption and VCO_2 is the rate of carbon dioxide production in $L \cdot min^{-1}$. The mean of the calculated EE in the last 2 min of each walking stage was used for subsequent analysis.

Part 2

Ten overweight or obese adults (5 females and 5 males) were recruited (age 44 ± 13 years, stature 174 ± 9 cm, BM $92.4. \pm 16.2$ kg; BMI 30.4 ± 4.0 kg/m^2, waist to hip ratio 0.87 ± 0.06). The test protocol consisted of a self-paced walk around a 3 km route in a local country park. Participants were instructed to walk at a comfortable walking speed that they could maintain for at least 30 mins. Walking speed was tracked using a Garmin 405 GPS (Garmin International Inc, USA) and the average walking speed for the participants was 5.9 ± 0.5 km$\cdot$h^{-1}. The EE was measured as before by indirect calorimetry, this time using a portable metabolic analyser (K4b^2, Cosmed, s.r.l., Rome, Italy), which was calibrated prior to each test as per the manufacturer's guidelines. The accuracy of the K4b^2 was assessed in a separate study (Howe, Matzko, Piaser, Pitsiladis & Easton, 2014) and was found to provide accurate measurements of minute ventilation, VO_2 and VCO_2 compared to the laboratory based metabolic cart (Oxycon Pro, Carefusion, UK) used in Study 1. The EE was calculated as before and the mean of the whole walking test was used for subsequent analysis with the exclusion of the first 3 min of data due to non-attainment of steady state values.

Accelerometer and Heart Rate

Prior to all tests, the GT3X+ was initialised using the device software (Actilife 5, ActiGraph, LLC, Fort Walton Beach, FL). The GT3X+ was placed inside a neoprene pouch attached to an elasticised waist-band which was then placed on the participant's right hip on the mid-auxiliary line for the duration of the experiment in both parts of the study. The GT3X+ was set to collect data using a 1 second epoch and reintegrated to a 60 second epoch during the analysis process. HR was measured continuously throughout each experiment using a HR strap fitted around the participant's chest and the data transmitted via telemetry (Polar Electro Oy, Kempele Finland). The mean HR and AC data were time-matched with the respiratory variables for subsequent analysis. EE was estimated using the Freedson equation based on AC from the vertical axis (Freedson et al., 1998) and the VM3 equation, which utilises AC from all three axes of motion (Sasaki et al., 2011).

Data Analysis

Data are presented as mean ± SD. In Part 1 differences between predicted (Freedson and VM3 equations) and criterion method (indirect calorimetry) EE were assessed by two-way repeated measured ANOVA (for EE assessment method and walking speed) followed by *post hoc* paired samples t-tests with Bonferroni adjustment. The mean VO_2 in $mL \cdot kg^{-1} \cdot min^{-1}$ and mean GT3x+ VM counts·min^{-1} obtained at each walking speed were used to derive PA intensity classification cut-points. The Metabolic Equivalent of Task (MET) values for each stage of the exercise test were calculated by dividing the steady state VO_2 by 3.5 $mL \cdot kg^{-1} \cdot min^{-1}$. Using simple linear regression, the VM cut-points were established from the MET values for moderate, vigorous, and very vigorous PA. Cross-validation of the regression equation was undertaken using a delete-one jack-knife approach (21) comparing measured METS to predicted METS and differences assessed using two-way repeated measured ANOVA (for METs assessment method and walking speed).

9

Separate novel EE prediction equations were generated for males and females by linear and multiple linear regression using combinations of VM, BM and HR. Cross-validation of these equations and differences between measured (indirect calorimetry) and predicted (novel EE equations) were assessed as previously described. Correlations between EE assessment methods were calculated using Pearson correlation coefficients (r). Bland and Altman (1986) analysis was used to demonstrate agreement between EE assessment methods and 95% limits of agreement (LOA) were calculated as mean $\pm$ 1.96 SD of the difference between methods. The standard error of the estimate (SEE) was calculated using the square root of the error sum of squares divided by the degrees of freedom.

In Part 2, differences between measured (indirect calorimetry) and predicted (novel equations) EE and METs were assessed using a paired samples t-test. Correlation and agreement between EE and METs assessment methods was assessed as previously described. The null hypothesis was rejected when $P < 0.05$. All data were analysed using PASW Statistics 18 (SPSS Inc., Chicago).

Results

Part 1

Speed was significantly correlated with VM, HR, measured EE and METs ($r = 0.77$, $r = 0.48$, $r = 0.57$, $r = 0.77$ respectively, all $p < 0.01$). The Freedson and VM3 equations both significantly overestimated EE at all walking speeds, with the exception of 4 km·h^{-1} where there was no difference ($p = 0.12$) between the Freedson equation estimated and measured EE (Fig. 1). The Freedson and VM3 prediction equations were both significantly correlated with measured EE ($r = 0.75$, $p < 0.01$ and $r = 0.76$, $p < 0.01$ respectively). Bland and Altman (1986) analysis demonstrated a poor level of agreement between the two existing prediction equations and measured EE, with the Freedson equation overestimating measured EE by an

average of ~40% (mean bias 2.40 kcal·min^{-1} and 95% LOA –7.21 to 2.41 kcal·min^{-1}) and the VM3 equation overestimating EE by an average of ~31% (mean bias 1.65 kcal·min^{-1} and 95% LOA –4.79 to 1.50 kcal·min^{-1}).

The novel regression equation generated to predict METs from VM (counts·min^{-1}) was METs = (0.000437 × VM) + 1.743 (r^2 = 0.64, SEE = 0.46 METs) (Table 1). There were no differences between actual measurement of METs and predicted METs (p = 0.90). The mean differences between actual and predicted METs for each walking speed were −0.16, −0.20, −0.13, 0.14 and 0.48 METs at 4, 4.5, 5, 5.5 and 6 km·h^{-1}, respectively.

Novel predictions of EE using combinations of VM, BM and HR were significantly correlated with, and not different from, measured EE with the exception of the combined VM and BM equation which significantly overestimated EE at all walking speeds (Table 2). Bland and Altman (1986) analysis demonstrates good agreement between measured and predicted EE for the VM equation, the VM and HR equation and the VM, BM and HR equation with a mean bias and 95% LOA of –0.38 and –2.72 to 1.96 kcal·min^{-1}, –0.04 and –2.13 to 2.04 kcal·min^{-1}, and –0.08 and –1.70 to 1.87 kcal·min^{-1}, respectively (Fig. 2).

Part 2

The Freedson and VM3 equations both significantly overestimated actual EE during the external walk (p = 0.01 and p = 0.03 respectively). Bland and Altman analysis demonstrated a poor level of agreement between the two existing prediction equations and measured EE (Freedson equation: mean bias –3.23 kcal·min^{-1}, 95% LOA –6.32 to –0.13 kcal·min^{-1}; VM3 equation: mean bias –2.62 kcal·min^{-1}, 95% LOA –4.90 to –0.33 kcal·min^{-1}). There were no differences between measured METs and METs predicted from the novel regression equation (p = 0.17) and the two measurement methods were significantly correlated (r = 0.78, p =

0.01). The mean difference between measured and predicted METs was –0.25 METS (95% LOA –1.27 to 0.78 METs) with a SEE of 0.54. The novel predictions equation using VM and BM significantly overestimated measured EE during the external walk ($p < 0.01$) and the equation using VM and HR data significantly underestimated EE ($p = 0.01$, Table 3). Equations using VM alone or a combination of VM, BM and HR data were not different from measured EE ($p = 0.53$, $p = 0.17$ respectively). There was moderate agreement between the VM equation and measured EE (mean bias –0.34 kcal/min, 95% LOA –3.57 to 2.98 kcal·min^{-1}, SEE 1.74) and good agreement between the combined VM, BM and HR equation and measured EE (mean bias –0.34 kcal·min^{-1}, 95% LOA –0.92 to 1.49 kcal·min^{-1}, SEE 0.65).

Conclusion

The current study has established new PA cut-points for the GT3X+ accelerometer (Table 1) that are specific for overweight and obese adults. These cut-points, based on walking speed, may be used for objective PA measurement in overweight and obese males and females. There is a large body of research that have generated other accelerometer cut-points in children and mixed cohort adults (Welk et al., 2004; Heil, 2006; Pfeiffer et al., 2006; Sasaki et al., 2011). The need for population specific and activity specific cut-points is crucial for accurate and objective assessment of time spent undertaking PA. There can be a large degree of variability not only between different accelerometer brands, but also between accelerometer positon on the body, body composition, stride length and frequency, as well as mechanical efficiency of the individual (Dellava & Hoffman, 2009). Therefore the cut-points generated from accelerometers worn on the hip in this study may provide a useful tool for assessing specifically walking activity in overweight and obese populations and aid in future health based research and intervention programmes.

A further aim of this study was to develop gender and population-specific EE prediction equations, and examine the accuracy of existing equations. The majority of established prediction equations are generated from mixed gender cohorts, which fail to account for any inherent differences in EE between genders. In the present study the Freedson and VM3 equations overestimated EE in both male and female cohorts. These findings suggests that there is not a "one size fits all equation" for predicting EE.

One evident limitation of using accelerometers alone to assess PA or EE is that they are unable to detect any load-carrying activity (Rennie, Hennings, Mitchell & Wareham, 2001; Crouter et al., 2007; Fudge et al., 2007). Of course, this is particularly relevant for overweight and obese individuals with excess BM. To counter this, it has also been suggested that an improvement in EE estimations can be achieved by incorporating a physiological variable

such as HR into accelerometer prediction equations (Haskell et al., 1993; Rennie et al., 2001; Strath, Bassett, Swartz, & Thompson, 2001; Crouter et al., 2007). Individual HR variance between different participants as well as between genders may also be a reason why gender specific equations are more accurate at predicting EE than mixed gender equations. Previous research (Crouter et al., 2007) identified limitations of using the mean HR response of a participant cohort as it fails to identify individual HR variance. It was therefore suggested that future studies investigate the use of HR variance in EE prediction equations to address individual HR variability (Crouter et al., 2007). The potential flaws of these equations were that they were generated in a controlled laboratory environment at fixed walking speeds and therefore there is a risk they would not be valid for use in the external environment. Part 2 of the present addressed this using a 3 km self-paced walk in the field and suggested that the prediction equation combining VM, BM and HR provided the most accurate estimation of EE. However, the use of prediction equations to assess EE has been widely questioned due to the reported inaccuracy across a wide range of activities, intensities and populations (Lyden et al., 2011). Sasaki and colleagues validated the VM3 equation used by the GT3X+ and found no significant difference between measured and predicted EE (SEE of 1.43 kcal·min^{-1}) (Sasaki et al., 2011).

In the present study, the VM, BM and HR gender specific equation provided the most accurate estimation of EE with a lower SEE of 0.77 kcal·min^{-1}. This equation is a substantial improvement on the VM equation (Sasaki et al., 2011) in overweight and obese adults and therefore may provide a more accurate estimation of EE in this population. In addition, mixed gender equations using only VM and BM also demonstrate a lower SEE than previous prediction equations (Sasaki et al., 2011). However, the data from the present series of studies suggests that the addition of HR to VM and BM will strengthen the accuracy of these predictions. Nevertheless, there is still a risk of inaccurate results at the individual level and a

gold standard measurement of EE (doubly-labelled water or indirect calorimetry) should be still used where appropriate.

The greater predictive power of gender specific prediction equations observed in the current study may be due to the differences in EE between males and females. Hormonal changes in women and the increased metabolic cost of walking in males may account for the measured differences in EE between males and females (Webb, 1986). Variations in the mechanical efficiency of walking between genders may also impact on EE with stride length approximately 15 cm longer in males than females (Brooks, Gunn, Withers, Gore & Plummer, 2005).

A potential limitation to the present study is the small sample size in Study 2; however this allowed the accuracy of the equations to be assessed in a small group of individuals, which may be more applicable for future intervention studies. Subsequently, the ability of the VM, BM and HR equation to accurately predict EE in a small sample size supports its potential use in the field.

In conclusion, this study has provided specific accelerometer cut-points for walking exercise in overweight and obese adults using the GT3x+ accelerometer, allowing researchers to more objectively monitor PA in this population. This study has also generated novel gender specific EE prediction equations combining VM, BM and HR, which may supply a more inexpensive and convenient method to estimate EE. Although ambulatory cut-points offer similar patterns to that of free living (Watson et al., 2014) these equations need to be validated over a range of different lifestyle activities, such as jogging, gardening and other household tasks to assess its usability in long-term intervention programmes. Finally and in line with previous research (Crouter et al., 2006; Howe & Easton, 2011), both the Freedson and VM3 equations used by the GT3X+ tri-axial accelerometer are unsuitable for predicting

EE during both treadmill and overground walking in overweight and obese individuals, as they significantly overestimate EE.

References

Bland, J. M., & Altman, D. (1986). Statistical methods for assessing agreement between two methods of clinical measurement. *The Lancet, 327*(8476), 307-310.

Brooks, A. G., Gunn, S. M., Withers, R. T., Gore, C. J., & Plummer, J. L. (2005). Predicting walking METs and energy expenditure from speed or accelerometry. *Medicine and Science in Sports and Exercise, 37*(7), 1216-1223.

Chen, K. Y., Acra, S. A., Donahue, C. L., Sun, M., & Buchowski, M. S. (2004). Efficiency of walking and stepping: relationship to body fatness. *Obesity Research, 12*(6), 982-989.

Colley, R. C., & Tremblay, M. S. (2011). Moderate and vigorous physical activity intensity cut-points for the Actical accelerometer. *Journal of Sports Sciences, 29*(8), 783-789.

Crouter, S. E., Clowers, K. G., & Bassett, D. R. (2006). A novel method for using accelerometer data to predict energy expenditure. *Journal of Applied Physiology, 100*(4), 1324-1331.

Crouter, S. E., Churilla, J. R., & Bassett, D. R. (2007). Accuracy of the Actiheart for the assessment of energy expenditure in adults. *European Journal of Clinical Nutrition, 62*(6), 704-711.

Dellava, J. E., & Hoffman, D. J. (2009). Validity of resting energy expenditure estimated by an activity monitor compared to indirect calorimetry. *British Journal of Nutrition, 102*(1), 155-159.

Freedson, P. S., Melanson, E., & Sirard, J. (1998). Calibration of the Computer Science and Applications, Inc. accelerometer. *Medicine and Science in Sports and Exercise, 30*(5), 777-781.

Fudge, B. W., Wilson, J., Easton, C., Irwin, L., Clark, J., Haddow, O., & Pitsiladis, Y. P. (2007). Estimation of oxygen uptake during fast running using accelerometry and heart rate. *Medicine and Science in Sports and Exercise, 39*(1), 192-198.

Godfrey, A. C., Conway, R., Meagher, D., & ÓLaighin, G. (2008). Direct measurement of human movement by accelerometry. *Medical Engineering & Physics, 30*(10), 1364-1386.

Haskell, W. L., Yee, M. C., Evans, A. N., & Irby, P. J. (1993). Simultaneous measurement of heart rate and body motion to quantitate physical activity. *Medicine and Science in Sports and Exercise, 25*(1), 109-115.

Hawkins, M. S., Storti, K. L., Richardson, C. R., King, W. C., Strath, S. J., Holleman, R. G., & Kriska, A. M. (2009). Objectively measured physical activity of USA adults by sex, age, and racial/ethnic groups: a cross-sectional study. *International Journal of Behavioral Nutrition and Physical Activity, 6*(1), 1.

Heil, D. P. (2006). Predicting activity energy expenditure using the Actical® activity monitor. *Research Quarterly for Exercise and Sport, 77*(1), 64-80.

Howe, C., & Easton, C. (2011). Energy expenditure estimation during walking in overweight and obese adults from the ActiTrainer accelerometer and heart rate. [Abstract]. *Journal of Sports Sciences, 29.*

Howe, C. C., Matzko, R. O., Piaser, F., Pitsiladis, Y. P., & Easton, C. (2014). Stability of the K4b2 portable metabolic analyser during rest, walking and running. *Journal of Sports Sciences, 32*(2), 157-163.

Johannsen, D. L., Calabro, M. A., Stewart, J., Franke, W., Rood, J. C., & Welk, G. J. (2010). Accuracy of armband monitors for measuring daily energy expenditure in healthy adults. *Medicine and Science in Sports and Exercise, 42*(11), 2134-2140.

Luke, A., Maki, K. C., Barkey, N. A., Cooper, R., & McGee, D. A. (1997). Simultaneous monitoring of heart rate and motion to assess energy expenditure. *Medicine and Science in Sports and Exercise, 29*(1), 144-148.

Lyden, K., Kozey, S. L., Staudenmeyer, J. W., & Freedson, P. S. (2011). A comprehensive evaluation of commonly used accelerometer energy expenditure and MET prediction equations. *European Journal of Applied Physiology, 111*(2), 187-201.

McMinn, D., Acharya, R., Rowe, D. A., Gray, S. R., & Allan, J. L. (2013). Measuring activity energy expenditure: accuracy of the GT3X+ and actiheart monitors. *International Journal of Exercise Science, 6*(3), 217-229.

Pfeiffer, K. A., Mciver, K. L., Dowda, M., Almeida, M. J., & Pate, R. R. (2006). Validation and calibration of the Actical accelerometer in preschool children. *Medicine and Science in Sports and Exercise, 38*(1), 152-157.

Rennie, K. L., Hennings, S. J., Mitchell, J., & Wareham, N. J. (2001). Estimating energy expenditure by heart-rate monitoring without individual calibration. *Medicine and Science in Sports and Exercise, 33*(6), 939-945.

Richardson, C. R., Newton, T. L., Abraham, J. J., Sen, A., Jimbo, M., & Swartz, A. M. (2008). A meta-analysis of pedometer-based walking interventions and weight loss. *The Annals of Family Medicine, 6*(1), 69-77.

Sasaki, J. E., John, D., & Freedson, P. S. (2011). Validation and comparison of ActiGraph activity monitors. *Journal of Science and Medicine in Sport, 14*(5), 411-416.

Strath, S. J., Bassett, D. R., Swartz, A. M., & Thompson, D. L. (2001). Simultaneous heart rate-motion sensor technique to estimate energy expenditure. *Medicine and Science in Sports and Exercise, 33*(12), 2118-2123.

U.S. Department of Health and Human Services, & US Department of Health and Human Services. (2008). *Physical activity guidelines for Americans*. Washington, DC: US Department of Health and Human Services.

Watson, K. B., Carlson, S. A., Carroll, D. D., & Fulton, J. E. (2014). Comparison of accelerometer cut points to estimate physical activity in US adults. *Journal of Sports Sciences, 32*(7), 660-669.

Webb, P. (1986). 24-hour energy expenditure and the menstrual cycle. *The American Journal of Clinical Nutrition, 44*(5), 614-619.

Weir, J. D. V. (1949). New methods for calculating metabolic rate with special reference to protein metabolism. *The Journal of Physiology, 109*(1-2), 1.

Welk, G. J., Schaben, J. A., & Morrow Jr, J. R. (2004). Reliability of accelerometry-based activity monitors: a generalizability study. *Medicine and Science in Sports and Exercise, 36*(9), 1637-1645.

Table 1. Vector magnitude activity count cut-points for physical activity intensity levels.

Intensity	MET Range	VM (counts·min^{-1})
Moderate	3.00–5.99	3454–7555
Vigorous	6.00–8.99	7556–11669
Very vigorous	>8.99	>11699

Where MET is the metabolic equivalent and VM is the vector magnitude

Table 2. Comparison of predicted energy expenditure from novel regression equations with indirect calorimetry reference method during a laboratory-based incremental walking test.

Gender Specific Prediction Equation	Comparison with Reference Method
VM Males: $(0.00045 \times VM) + 4.028$ Females: $(0.001 \times VM) + 1.336$	$p = 0.33, r = 0.66,$ SEE $= 1.20$
VM and BM Males: $(0.001 \times VM) + (0.062 \times BM) - 2.711$ Females: $(0.001 \times VM) + (0.048 \times BM) - 1.642$	$p < 0.01, r = 0.75,$ SEE $= 1.05$
VM and HR Males: $(0.00027 \times VM) + (0.039 \times HR) + 1.062$ Females: $(0.00032 \times VM) + (0.068\ HR) - 3.986$	$p = 0.92, r = 0.74,$ SEE $= 1.06$
VM, BM and HR Males: $(0.00046 \times VM) + (0.007 \times HR) + (0.05 \times BM) - 2.325$ Females: $(0.00029 \times VM) + (0.052 \times HR) + (0.039 \times BM) - 5.091$	$p = 0.97, r = 0.82,$ SEE $= 0.91$

Where BM is body mass, HR is heart rate and VM is the vector magnitude of the accelerometer counts. p and r values indicate the difference and correlation between measured and predicted energy expenditure. SEE is the standard error of the estimate.

Table 3. Comparison of predicted energy expenditure from novel regression equations with indirect calorimetry reference method during a self-paced external walk.

Equation	Difference	Correlation	SEE	Mean Bias (kcal·min^{-1})	95% LOA (kcal·min^{-1})
VM	$p = 0.53$	$r = 0.72$	1.74	−0.34	−3.57 to 2.89
VM and BM	$p < 0.01$	$r = 0.90$	0.89	−2.68	−4.70 to −0.66
VM and HR	$p = 0.01$	$r = 0.86$	1.05	0.99	−0.96 to 2.93
VM, BM and HR	$p = 0.17$	$r = 0.95$	0.65	0.29	−0.92 to 1.49

Where BM is body mass, HR is heart rate and VM is the vector magnitude of the accelerometer counts. p and r values indicate the difference and correlation between measured and predicted energy expenditure. SEE is the standard error of the estimate and 95% LOA is 95% limits of agreement.
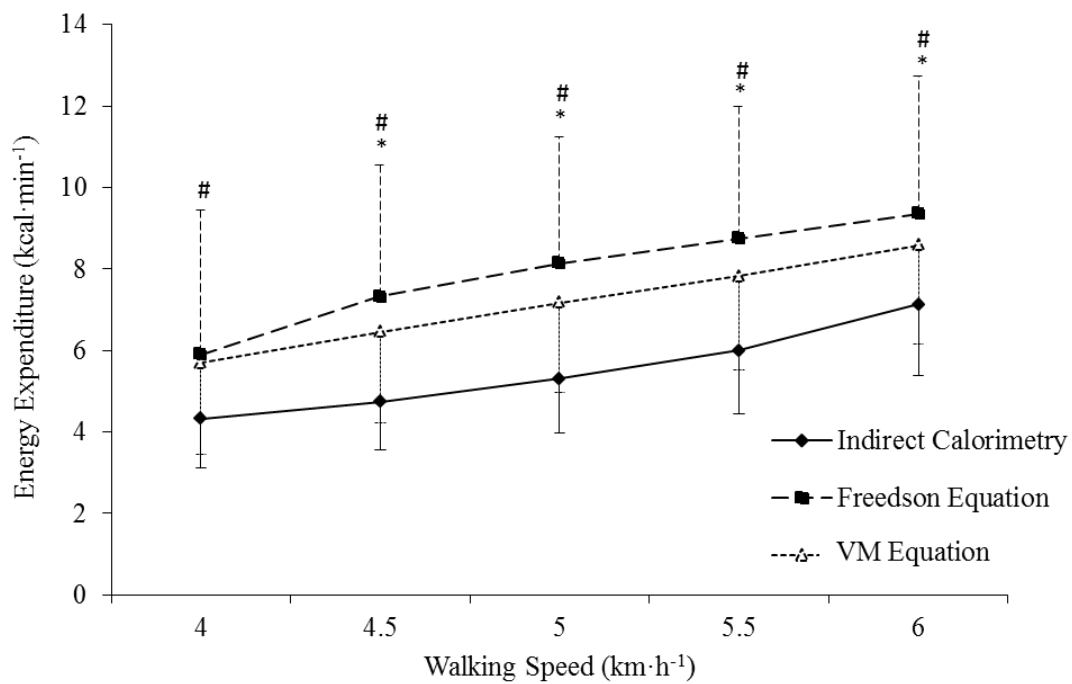
Figure 1: Measured (indirect calorimetry) *vs.* predicted (accelerometer derived Freedson and VM regression equations) EE during a laboratory-based incremental walking test. Data presented as the mean ± s.d. * indicates significant difference between indirect calorimetry and the Freedson equation and # indicates significant difference between indirect calorimetry and the VM equation ($p < 0.05$).
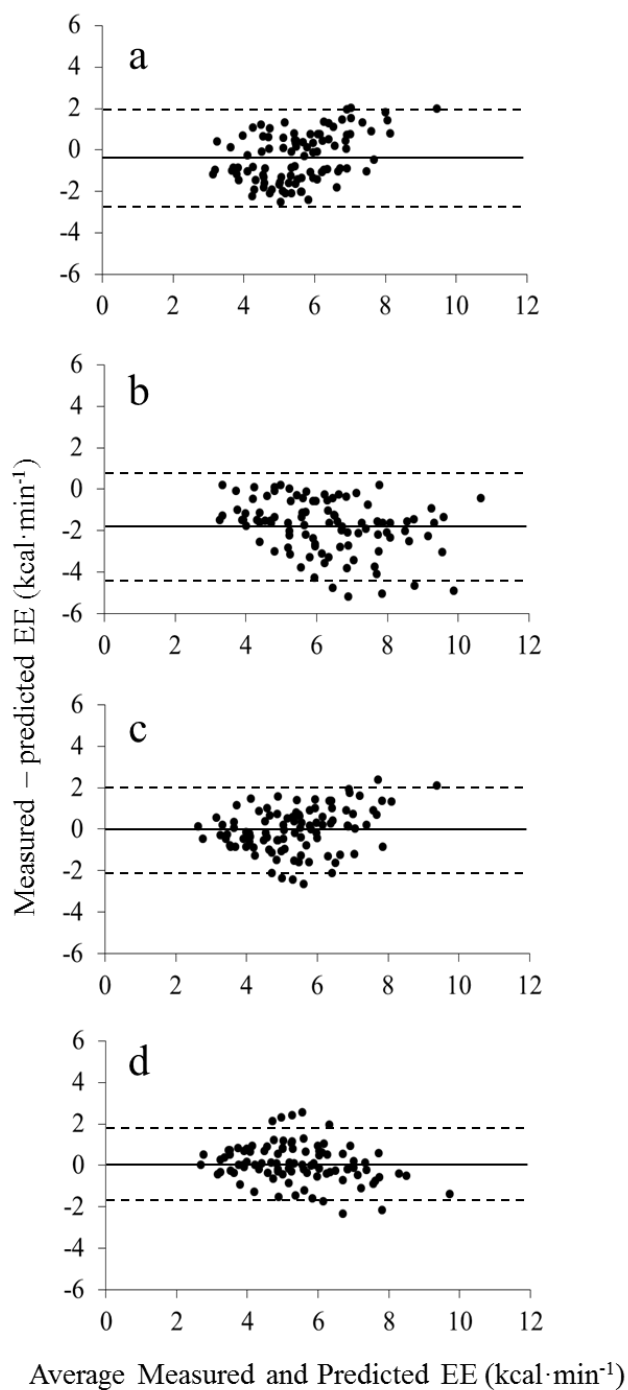
Figure 2: Bland & Altman plots of measured EE (indirect calorimetry) vs. predicted EE during a laboratory-based incremental walking test with mean difference (solid line) and 95% limits of agreement (dashed lines): (a) linear regression equation using VM activity counts, (b) multiple regression equation using VM and BM, (c) multiple regression equation using VM and HR, (d) multiple regression equation using VM, BM and HR.