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Accuracy of Accelerometer Regression Models in Predicting Energy Expenditure and METs in Children and Youth

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Abstract

This study examined the validity of commonly used regression equations for the Actigraph and Actical accelerometers in predicting energy expenditure (EE) in children and adolescents. Sixty healthy (8–16 yrs) participants completed four treadmill (TM) and five self-paced activities of daily living (ADL). Four Actigraph (AG) and three Actical (AC) regression equations were used to estimate EE. Bias (±95% CI) and root mean squared errors were used to assess the validity of the regression equations compared with indirect calorimetry. For children, the Freedson (AG) model accurately predicted EE for all activities combined and the Treuth (AG) model accurately predicted EE for TM activities. For adolescents, the Freedson model accurately predicted EE for TM activities and the Treuth model accurately predicted EE for all activities and for TM activities. No other equation accurately estimated EE. The percent agreement for the AG and AC equations were better for light and vigorous compared with moderate intensity activities. The Trost (AG) equation most accurately classified all activity intensity categories. Overall, equations yield inconsistent point estimates of EE.

The health benefits of regular physical activity (PA) have been well established in adults (26). Less data are available on these associations in children and adolescents and what has been reported is inconsistent (26). It has been suggested that the inconsistent results may be due to variations in the methods used to characterize PA dose (22). The variations in the methods used to assess PA impedes researchers and policy makers ability to validly document the prevalence of PA, determine if children are meeting PA recommendations, and test the effectiveness of interventions to increase PA.

In children, PA can be assessed by subjective measures (e.g., self-report diaries or questionnaires) or objective measures (e.g., direct observation, doubly-labeled water, heart rate monitoring, and accelerometry; 16, 17, 20). Large-scale prospective studies have relied mostly on self-reports to quantify PA due to their low cost and ease of use. Self-reports however, do not provide an objective measure of PA since they depend on children and adolescents to report and/or recall their past PA (8,28). Due to the inherent problems of self-reported PA in children and adolescents and the high cost and participant burden associated

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with direct observation, doubly-labeled water and heart rate monitoring, more studies are using accelerometers to provide an objective method for quantifying free-living PA (8,28).

Studies utilizing accelerometers to objectively quantify PA in field-based studies are faced with significant challenges in deciding which accelerometer to use and how to process and/or interpret the accelerometer data. Although there are several commercially available accelerometers, the two models that are most frequently used are the Actigraph (AG) and the Actical (AC). Accelerometers measure the acceleration associated with body movement and accelerometer output is expressed as total acceleration (counts) over a user specified unit of time (i.e., counts·min^{-1}). However, the methods used by the different monitors to generate counts·min^{-1} (cpm) vary widely making it difficult to compare across monitors. In addition, researchers need to decide how to process the accelerometer cpm data into physiologically meaningful outcomes such as energy expenditure (EE, expressed as kcal·min^{-1}or METs) or estimates of PA intensity (i.e., sedentary, light, moderate or vigorous). Typically in calibration studies, regression analyses are used to translate the accelerometer counts output into point estimates of EE and/or to detect different activity intensity levels using accelerometer cut-points. In the literature, different cut-points are used to define PA intensities [e.g., moderate-to-vigorous physical activity (MVPA)]. Discrepancies in the accelerometer cut-point for MVPA can lead to different estimates of the amount of time children spend engaged in MVPA and skew the association between PA and various health outcomes (9).

The discrepancies in accelerometer cut-points are due to differences in the regression models used to generate point estimates of EE and cut-points from accelerometer counts. Currently, there are several published regression equations for both the AG and AC accelerometers. All of the equations were developed in laboratory settings and differed considerably with respect to type of activity, type of locomotion, and age range and gender of the participants. A few studies have examined the accuracy of the regression equations in an independent sample (1,6,12,25). However, these studies have generally focused on one monitor, or have been limited by a small sample size or narrow range of activities. For example, Trost et al. examined the validity of three AG regression equations in children and adolescents and found that the equations were not accurate for predicting EE but were satisfactory in estimating activity intensity (25). The only activities examined by Trost et al. were sustained walking and running, thus it is not known if these prediction equations are valid for a broader array of activities. To the best of our knowledge the most commonly used equations for AG and AC monitors have never been cross validated within the same sample to determine their accuracy in predicting EE and PA intensity in a broad range of activities. The purpose of this study was to examine the validity of several commonly used regression equations for predicting EE and estimating PA intensity for the AG and AC, in children and adolescents across a broad range of activities.

Methods

Participants

Healthy, 8–11 year old children (n = 30) and 12–16 year old adolescents (n = 30) were recruited from local schools in Amherst, MA, and the surrounding communities. Participants were free from cardiovascular or metabolic diseases or physical impairments that would interfere with participation in PA and were not taking any medications that would affect metabolism (e.g., Ritalin or Concerta). A parent/guardian provided an institutionally approved signed informed consent and participants provided assent to participate in the study.

Measures and Activity Protocol

Anthropometric and Resting Metabolic Measures—Participants reported to the Physical Activity and Health Laboratory following a 3-hr fast. Body weight was measured twice in light clothing, to the nearest 0.1 kg, using a calibrated portable digital scale (Scaletronix 5602 Model scale; White Plains, NY). Standing height was measured twice to the nearest millimeter, using a portable direct reading stadiometer (Shorr Height Measuring Board; Olney, MD). Body mass index (BMI), was computed as the body weight (kg) divided by height squared (meters^2). After 10 min of quite rest in a supine position in temperature-controlled room, resting metabolic rate (RMR) was assessed using the MedGem metabolic analyzer (MicroLife, USA; Dunedin, FL).

Activity Protocol—Following the RMR measurement, participants were offered a 150 kcal snack consisting of a cereal bar and juice or water. Participants then completed the treadmill (TM) and self-paced activities of daily living (ADL) protocols in balanced order. For the TM protocol, participants performed four 7-min TM activities at speeds from 3.22 to 8.05 kph at 0% and 3% grade with four minutes of rest between bouts. The order of the TM activities was balanced across participants. The ADLs (common leisure and sports activities) protocol consisted of 10 min of self-paced walking with a backpack (over level ground indoors, 4.54 kg load for children and 6.8 kg load for adolescents), riding a bicycle, basketball, Wii Tennis, and either crafts (children) or board games (adolescents). Each participant was asked to complete the ADLs "*as they would in their own home*" with minimal instruction to allow for individual variability in accomplishing each task. The order of the ADL activities was also balanced across participants. The activities performed in this study were selected because they represent a broad range of activities that both urban and suburban children and adolescents perform in their free-living environments. Lyden et al. recently published an in-depth description of the activity protocol (15).

Participants completed an average of 8.7 activities (range = 7–9). Seventeen activities were not performed for various reasons, including 1) inability to complete the task (e.g., running at 5 mph was too intense or could not ride a bicycle), 2) scheduling conflicts (two children did not complete the basketball activity) and 3) researcher error (in two instances the researcher provided the participant a backpack with incorrect weight). In addition, metabolic data were not available for eight activities (sample line occlusion), resulting in a total of 515 possible participant-by-activity comparisons used for data analysis.

Indirect Calorimetry—During each activity, total EE was measured using the Oxycon Mobile portable metabolic analyzer (Cardinal Health; Yorba Linda, CA). The Oxycon Mobile, a light-weight device worn as a backpack, is a valid and reliable system for measuring respiratory gas exchange in the field (27). The Oxycon Mobile was calibrated before the TM and ADL protocols. The first 2 min and last 10 s of Oxycon Mobile data for each activity were not used in the analysis. The remaining data were averaged to determine the total EE during the activity expressed as kcal·min^{-1}. In cases when the participant did not complete the entire activity, a minimum of 60 s of valid data were required to be included in analyses. Average measured VO_2 was determined and converted to relative VO_2 (ml·kg^{-1}·min^{-1}) and then to METs. Relative VO_2 was converted to METs by dividing by the individual's measured RMR for all analyses. Physical activity energy expenditure (PAEE) was computed by subtracting the individually measured RMR from total EE.

Accelerometry—The Actigraph GT1M (ActiGraph, Pensacola, FL), a capacitance uniaxial device, measures acceleration signals in the vertical plane between 0.05–2.5 g at a sampling rate of 30 Hz. The GT1M has been validated for estimating EE in children of all ages (6,18,25). The AG was worn on the nondominant hip on the anterior superior iliac crest in line with anterior axillary. The AG was initialized for collecting data in 1-s epochs and average cpm were computed for each activity. The AC (Actical, Mini Mitter, Bend, OR), also validated for this population (4,11,18), was worn on the nondominant hip positioned lateral to the AG monitor. The AC monitor is a piezoelectric omni-directional device that measures acceleration signals in multiple planes between 0.5–3 g at a sampling rate of 32 Hz. The AC accelerometer was initialized to collect data in 15-s epochs, the smallest epoch length available for this device.

For each activity, the first 120 s were eliminated to ensure steady state had been reached and the last 10 s were eliminated to minimize any researcher error in timing synchronization between the monitor and the metabolic measurements. The remaining valid data were used for analysis. For each activity, accelerometer data were converted to average counts·min^{-1} and entered appropriately into each equation to predict EE. Each activity was then classified as light (<4 METs), moderate (4–6.99 METs) or vigorous (≥7 METs) intensity based upon measured METs (10,19,21,23). For the equations that predict EE in kcals (Puyau, Trost, and Heil), kcals were first converted to METs and then classified into intensity categories. Four AG and three AC prediction models were examined (Table 1).

Statistical Analysis

To assess the validity of the prediction models we compared predicted EE to measured EE using two statistical tools: bias (95% confidence interval [CI]) and root mean squared error (RMSE). RMSE is the square root of the average squared difference between predicted and measured EE and is an expression of the magnitude of the absolute difference between predicted and measured EE. Bias is the average difference between predicted EE and measured EE and describes the direction of the predicted error. A positive bias indicates an overestimation of EE by the prediction model, while a negative bias indicates an underestimation of EE by the prediction model. We used the 95% CI's of the bias to determine significance. If the lower and upper intervals spanned zero, predicted EE was not significantly different than measured EE at α=0.05. These comparisons are presented in four ways: 1) all activities combined 2) all TM activities combined, 3) all ADLs combined and 4) for each individual activity. The agreement between actual and predicted activity intensity classification were determined using kappa statistics (κ). Levels of agreement are considered

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slight, fair, moderate, substantial, and almost perfect with κ = 0.00–0.20, 0.21–0.40, 0.41–0.60, 0.61–0.80, and 0.81–1.00, respectively (13).

In the current study, the results are presented for all activities combined and separately for TM and ADL activities. This is to assist researchers conducting field base studies (i.e., observational and/or intervention studies) in choosing the most accurate monitor-specific equation for their study outcome. For example, if the majority of the activities being performed in a particular study consist of ADL activities, then an equation that performs reasonably well at estimating EE for ADLs should be selected. In general, the accuracy of an equation in estimating EE for one activity is less important simply because most of the time, researchers use the equations on groups of activities and not as point estimates of a single activity. We have provided results for individual activities to help readers interpret the findings and to see which activity produces most of the errors associated with an equation.

Results

The physical characteristics of the participants (children, 8–11 yrs; *n* = 32 and adolescents 12–16 yrs; *n* = 28) are presented in Table 2. The average BMI for the group was 19.7 kg·m^{-2}, with 23% of the total sample (children (*n* = 9); adolescents (*n* = 5)) classified as overweight or obese (BMI ^{3}85th percentile). The mean (± *SD*) measured and predicted energy costs for children and adolescents are reported in Table 2.

On average, participants completed 8.7 activities. After data cleaning, the mean (± *SD*) time per activity was 5.75 ± 0.0 min. The mean (± *SD*) measured energy cost values across all activities for children and adolescents were 3.52 ± 1.55 MET's (3.48 ± 1.66 kcal·min^{-1}) and 4.27 ± 2.25 MET's (5.10 ± 2.82 kcal·min^{-1}), respectively. The mean (± *SD*) measured energy cost values for all treadmill activities combined for children and adolescents were 3.46 ± 0.76 MET's (3.38 ± 0.86 kcal·min^{-1}) and 5.06 ± 1.70 MET's (6.00 ± 2.03 kcal·min^{-1}), respectively and the mean (± *SD*) measured energy cost values for all ADL activities combined for children and adolescents were 3.57 ± 1.96 MET's (3.56 ± 2.07 kcal·min^{-1}) and 3.66 ± 2.44 MET's (4.40 ± 3.14 kcal·min^{-1}), respectively. The mean (± *SD*) energy cost values for children ranged from 1.50 ± 0.23 MET's (1.47 ± 0.31 kcal·min^{-1}; crafts) to 6.64 ± 1.35 MET's (3.62 ± 1.18 kcal·min^{-1}; basketball). The mean (± *SD*) energy cost values for adolescents ranged from 1.35 ± 0.30 MET's (1.60 ± 0.41 kcal·min^{-1}; board games) to 7.64 ± 1.82 MET's (9.32 ± 2.96 kcal·min^{-1}; basketball).

Tables 3, 4, 5 and 6 report the bias (predicted EE—measured EE; 95% confidence interval) and the RMSE across all activities combined, for all treadmill activities, for all ADL's and for each activity. For children, the Freedson (AG) model accurately predicted EE for all activities combined (Bias 0.1 METs; 95% CI 0.0, 0.3) and ADLs (Bias −0.2 METs; 95% CI −0.4, 0.0) and the Treuth (AG) model accurately predicted EE for treadmill activities (Bias 0.1 METs; 95% CI 0.0, 0.3). For adolescents, the Freedson model accurately predicted EE for treadmill activities (Bias 0.0 METS; 95% CI −0.2, 0.3) and the Treuth (AG) model accurately predicted EE for all activities (Bias −0.2 METs; 95% CI −0.4, 0.0) and for treadmill activities (Bias 0.1 METs; 95% CI −0.1, 0.3). In both children and adolescents, none of the AC equation accurately predicted EE across all activities, TM or ADL activities.

The percent agreement between the actual and predicted activity intensity classification ranged from 43.1% to 88.3% (Table 7). For the AG equations, the highest and lowest levels of agreement were observed for Trost (AG) equation for vigorous intensity [k = 0.55 (95% CI 0.46–0.65)] and Puyau (AG) equation for moderate intensity [κ = −0.009 (95% CI −0.9–0.07)], respectively. For the Actical equations, the highest and lowest levels of agreement were observed for Heil 1R for vigorous intensity [κ = 0.34 (95% CI 0.23–0.44)] and Puyau (AC) equation for low intensity [κ = −0.01 (95% CI −0.09–0.07)], respectively.

Discussion

There are several published regression equations for converting accelerometer output into EE or estimates of categories of PA intensity. However, the validity of these prediction models has never been compared in an independent sample performing a wide range of activities. Therefore, the purpose of this study was to examine the validity of several commonly used regression equations for predicting EE and estimating PA intensity from Actigraph and Actical accelerometer counts, in children and adolescents across a range of activity types and intensities. In the current study, across all activities (TM and ADLs) both the Actigraph and Actical equations produced mixed results and in general did not produce accurate point estimates of EE. All the equations demonstrated slight to fair agreement level in their ability to accurately classify activity intensity.

Actigraph

The Actigraph accelerometer is one of the most widely used accelerometers in epidemiological studies and several equations have been developed to reduce its data. The Freedson (AG) et al. (7) equation was the first equation developed and most widely used for reducing Actigraph data. The Freedson equation was developed on both children and adolescents (6–18 years) who performed TM activities only (two walking speed and one running speed). When comparing the results of the current study by age group, the Freedson equation accurately estimated TM EE in adolescents, but was only accurate for children's slow pace graded walking (2.0 mph 3% grade). All other TM activities performed by the younger age group were overestimated by 10–26%. Conversely, for the ADL activities, the Freedson equation accurately estimated EE in children, but underestimated EE in adolescents. Overall, for both children and adolescents, the equation did poorly in estimate EE for individual ADL activities. This is not surprising given no ADLs were performed in the development of the equation. Whereas for all activities (TM and ADL) combined; the Freedson equation accurately estimated EE in children and only slightly underestimated EE in adolescents by 9.3%.

The Treuth (AG) equation was developed in adolescent girls (10–18 years) performing TM activities ranging from 2.5 mph–5.0 mph plus a similar set of ADL activities as in the current study, such as playing seated games, self-paced walking, shooting baskets and bicycling (23). Although there were great similarities between the Treuth study and the current data, for all activities combined, the Treuth (AG) equation still underestimated EE in children by 5%, but accurately estimated EE in adolescents. However, when comparing the different activity types, it accurately estimated EE in both children and adolescents TM activity, but, surprisingly underestimated all ADL EE by 26.8%. Despite the similar ADLs between the Treuth and present study, the equation did poorly in estimating EE for ADLs. This is likely due to the nature of ADLs, in that they are self-paced and the same activity (i.e., playing basketball, walking while carrying a load) can be performed at varying intensities and in a number of different ways. However, with no significant gender differences for measured METs, but a significant gender difference in Treuth-estimated METs (boys 7.6% higher than girls), this may indicate that the addition of boys may have contributed, in part, to the poor performance of the Treuth equation in the current study.

In the current study, both the Trost (AG) and Puyau (AG) equations consistently underestimated EE for all activities combined, TM, and ADLs in both children and adolescents from 29.2–43.9%. It is difficult to make comparisons between the Trost and Puyau equations as to why the two equations did poorly in estimating EE in both children and adolescents since the activities used in both calibration studies are different from the current study. For example, The Trost (AG) equation was developed in 30 adolescent boys and girls (of varying weight status) between the ages of 10–14 years using treadmill walking and running. Whereas, the Puyau (AG and AC) equation was developed in 26 children and adolescents boys and girls (normal weight) between the ages of 6–16 years of age in a wide range of self-pace free-living activities and TM activities ranging in intensity [sedentary (Nintendo)—vigorous (self pace jogging)]. Interestingly, both the Freedson and Trost (AG) equations were developed on TM activities of varying intensity, however, the Freedson (AG) equation was better at estimating EE compared with the Trost equation. This may be due to the fact the Freedson equation was developed using a participant sample more similar in age to the current study. Similarly, one might expect the Puyau (AG) equation to perform well on the current data set given the similar samples used and the activities performed between the two studies. However, the Puyau study used a whole room calorimeter to measure EE. Whole room calorimeter system does not have the capacity for high sampling rates to account for sudden changes in PA intensity and confines the performance of the ADL activities within a small room. Therefore, the poor performance of the Puyau (AG) equation could be due to differences in the measurement techniques of the study and the restricted nature of ADLs.

Actical

Actical accelerometer is the second most widely used accelerometer in PA field-based research. The AC is an omnidirectional accelerometer, sensitive to movement in all planes. This has led some researchers to speculate that it may produce more accurate estimates of EE, especially in pediatric populations where movement can be more random and sporadic compared with adults. However, until recently the AC equations have not been tested in an independent sample. In the current study, all the AC equations consistently underestimated EE for all activities combined, TM, and ADLs in both children and adolescents by 9.2–36.7%. The AC also underestimated EE when activities were analyzed individually. Given that these inaccuracies were consistent across all participant subcategories (children vs. adolescents and boys vs. girls) it is possible that a simple correction factor applied to this equation might improve the estimates provided by the AC equations. Future studies are necessary to determine if such a correction factor can be effective.

Most accelerometer equations used to estimate EE are single regression equations. Simple regressions however, traditionally do not perform well across a wide range of activity types and intensities and are often not accurate at producing point estimates of EE for individual activities (14). Heil's two-regression AC model was developed in an attempt to improve EE estimates across a range of activity types and intensities. However, the equation uses the intensity of the activity (determined by a count cut-off) to direct the accelerometer counts to one of two regression equations. This method poses a problem because it is possible for two activities to have a similar intensity but different counts·min^{-1}. For example, in the current study the measured EE for walking while caring a load (6.8 kg) and bicycling was 4.10 ± 0.53 and 4.51 ± 1.52 METs, respectively, while the average cpm was 1727 ± 127 and 83 ± 37, respectively. Based on the Heil (AC) equation, the two activities will be classified as two different intensities and directed to different equations, thereby resulting in incorrect estimates of EE. In adults, Crouter et al., have used the coefficient of variation in AC counts to direct activities into appropriate equations rather than using the EE (2). Recently, Crouter et al. developed a similar method for use in children, however the method has yet to be tested in an independent sample of children and adolescents (3).

Researchers often add ADLs in calibration studies in their attempt to increase their accuracy in estimating EE (18,23). However, it is possible that the addition of ADLs could potentially impact the prediction of EE associated with TM loco-motor activities (i.e., walking and running). In addition, it is possible that most of the equations were not able to accurately predict the EE of ADLs due to the inclusion of bicycling and shooting baskets. In both of these activities, body motion is independent of activity intensity with certain upper (basketball shooting) or lower body movements (cycling) not detected by the activity monitor. For all equations, these activities had the largest bias in the current study. Treuth et al. (23) observed similar findings in their calibration study. Their prediction equations were more accurate in estimating activity intensities when they excluded bicycling in determining activity intensity thresholds.

Our study findings on the accuracy of the monitor equations are similar to what was reported by Trost et al., who examined the accuracy of three Actigraph equations (Freedson, Trost, and Puyau) in 45 children between the ages of 10–18 years performing five TM activities and found that the Freedson equation accurately estimated EE during fast running (24). However, unlike the current study, Trost et al. found that the Puyau equation accurately estimated EE associated with brisk walking. Overall, it is possible that variations in different features of the calibration studies such as participants age, type of activities (TM or ADL), and activity intensity could explain why only one equation accurately estimated EE for all activities. While participants age range and several of the activities performed in the current study were similar to those performed in Puyau et al. calibration study, the equation was not accurate in estimating EE in the present sample. Overall, none of the equations did very well at providing point estimate of EE for individual TM or ADL activities. For example, the Freedson equation did not do well at estimating EE for individual ADL activities; but it did well at estimating EE for all ADLs combined. These data suggest that when applied to free-living situations, where individuals perform a range of activity types and intensities, the Freedson equation will on average produce accurate EE estimates.

Accelerometer Classification of Activity Intensity

Using count cut-points, accelerometer prediction equations can classify activity into different PA categories (light, moderate, vigorous). In the literature, different cpm thresholds are used to define PA intensities such as MVPA. These discrepancies lead to different estimates of time spent in MVPA and can have implications for the established associations between PA and various health outcomes (9). In the current study, the equations' ability to accurately classify the activity intensity yields mixed results. The percent agreement between Actigraph equations was better for light (range, 54.3–77.7%) and vigorous (range, 81.7–88.3%) intensity activities compared with moderate intensity activities (range, 43.1–68.1%). The Trost (AG) equation most accurately classified all activity intensity categories. Similarly, the Actical equations performed better for light (79.7–80.4%) and vigorous (84.8–85.8%) intensity activities compared with moderate (54.6–61.5%). For both accelerometers, the Puyau (AG and AC) cut-points were the least accurate for classifying activity intensity. This is not surprising given the Puyau cut-points' consistent underestimation of EE for all subgroups and activities. Similar findings were observed in the study by Trost et al. (24), where it was reported that the Trost cut-points demonstrated the highest classification accuracy, while, the Puyau demonstrated the lowest classification accuracy.

Results from the current study illustrate the difficulty in estimating EE and classifying activity intensity using a single, hip mounted accelerometer. The addition of ADLs to calibration studies has improved EE estimates across a range of activity types and intensities (18,23), however activities that require minimal movement of one's center of mass or require substantial upper body movement continue to be difficult to measure (23). For example, in the current study bicycling and shooting baskets yield MET values that classify them as moderate and vigorous activities respectively, however their count values classify them as low and moderate intensity, respectively. These observations are in line with previous work by Evenson et al. (4) who reported that although the VO_2 for bicycling was the second highest observed in their study, the counts observed ranked it as sedentary activity.

The present study has several strengths such as the diverse representative sample with a wide age range and the use of both TM and ADL activities across a wide range of intensities. The findings should be interpreted with caution because although the ADLs were self-paced and participants were encouraged to perform the activities as they would during their daily lives, the activities were still performed in a laboratory setting and therefore not truly free-living conditions.

Summary and Conclusion

In conclusion, the study findings indicate that the regression equations for AG and AC accelerometers developed for children and adolescents yield inconsistent accuracy in estimating EE or activity intensity for all participants and activity types combined. For all activities combined, only the Freedson (AG) equation in children and the Treuth (AG) equation in adolescents produced accurate estimates of EE. The study results support the notion that the current regression cut-points are not able to consistently discriminate between activities that may have similar total acceleration features but different energy expenditure levels. In surveillance research, researchers are often not interested in point estimates of EE, but rather how well the monitor output distinguishes time in light (< 3 METs), moderate (3–5.99 METs) or vigorous (^{3} 6 METs) intensities. These estimates can be used to characterize habitual activity and establish relationships between PA and health. The Trost equation performed the best for classifying activities as light, moderate or vigorous.

The foundation of most calibration studies is that there is a linear relationship between acceleration and PA energy expenditure; thereby leading researchers to derive regression cut-points by comparing accelerometer counts (total acceleration over time) and oxygen consumption measured during specific dynamic activities (5). However, many nonlocomotive activities do no exhibit a linear relationship between movement at the hip (measured by the accelerometer) and EE. The energy cost of common activities for children such as sports, walking with a load, and household activities is not linearly related to movement at the hip. In addition, in children this linear relationship is confounded by growth (i.e., PA energy expenditure tends decrease as a function of maturation; 6). Therefore, future studies should consider developing different approaches to process accelerometer data such as neural networks and other machine learning approaches that do not depend on static linear relationships between motion and EE. In addition, it is important that new and old approaches be validated in free-living situations.

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Table 1

Prediction Equations

Study	Population	Prediction equation	Cut-points (cpm)
Actigraph			
Freedson et al. 1997 (7)	*N* = 80; 6–18 y; Boys and girls	MET = 2.757 +(0.0015 × cpm)—(0.08957 × age (y))—(0.000038 × cpm × age (y))	
Puyauetal. 2002 (18)	*N* = 26; 6–16 y; Boys and girls	$\text{Kcal}\cdot\text{kg}^{-1}\text{min}^{-1} = 0.0183 + (0.000010 \times \text{cpm})$	Light: <3200 Mod: 3200–8199 Vig: ≥8200
Treuth et al.2004 (23)	*N* = 74; 13–14 y; Girls only	MET = 2.01 + (0.000856 × cpm)	Light: <3000 Mod: 0–3000 Vig: ≥5200
Trost et al.1998 (24)	*N* = 30; 10–14 y Boys and girls	$\text{Kcal}\cdot\text{min}^{-1} = -2.23 + (0.0008 \times \text{cpm}) + (0.08 \times \text{wt (kg)})$	
Actical			
Heil et al. 2006 (11)	*N* = 24; 8–18 y; Boys and girls	1R^{+}: $\text{Kcal}\cdot\text{kg}^{-1}\cdot\text{min}^{-1} = 0.03411 + (1.27\text{E-}5 \times \text{cpm})$	
Heil et al.2006 (11)	*N* = 24; 8–18 y; Boys and girls	2R^{+}: $\text{Kcal}\cdot\text{kg}^{-1}\cdot\text{min}^{-1} = 0.01667 + (5.10\text{E-}5 \times \text{cpm})$ $\text{Kcal}\cdot\text{kg}^{-1}\cdot\text{min}^{-1} = 0.03534 + (1.135\text{E-}5 \times \text{cpm})$	
Puyau et al.2002 (18)	*N* = 26; 6–16 y; Boys and girls	$\text{Kcal}\cdot\text{kg}^{-1}\cdot\text{min}^{-1} = 0.00423 + (0.00031 \times \text{cpm})^{0.653}$	Light: <1500 Mod: 1500–6500 Vig: ≥6500

+ Heil 1R uses only one equation regardless of counts. The 2R uses the intensity (counts/min) of the activity to direct the accelerometer data to one of two equations.

Table 2

Group Comparisons

	All Subjects	Age Group		Gender	
		8–11 y	12–16 y	Male	Female
Participant Characteristics (mean± *SD*)					
N	60	32	28	30	30
Age (y)	11.5 ± 2.4	9.6 ± 1.1	13.6 ± 1.3	11.3 ± 2.3	11.7 ± 2.4
BMI ($kg{\cdot}m^{-2}$)	19.7 ± 4.1	18.5 ± 4.3[a]	21.1 ± 3.5[a]	20.6 ± 5.0	18.7 ± 2.7
RMR (kcal·day)	1549 ± 363	1407 ± 263[a]	1710 ± 398[a]	1682 ± 395[b]	1415 ± 276[b]
Measured Energy Cost of the Activities (mean± *SE*)					
METs	3.87 ± 0.1	3.52 ± 0.1[a]	4.27 ± 0.1[a]	3.87 ± 0.1	3.88 ± 0.1
Total EE ($kcal{\cdot}min^{-1}$)	4.25 ± 0.1	3.48 ± 0.1[a]	5.10 ± 0.2[a]	4.62 ± 0.2[b]	3.89 ± 0.1[b]
PAEE ($kcal{\cdot}min^{-1}$)	3.18 ± 0.1	2.51 ±0.1[a]	3.91 ± 0.2[a]	3.45 ±0.1[b]	2.91 ±0.1[b]
Actigraph-Predicted Energy Cost (mean± *SE*)					
Freedson (METs)	3.76 ± 0.1	3.65 ± 0.1	3.88 ± 0.1[*]	3.95 ± 0.1	3.58 ± 0.1[*]
Treuth (METs)	3.69 ± 0.1	3.34 ± 0.1	4.07 ± 0.1	3.82 ± 0.1	3.56 ± 0.1[*]
Trost ($kcal{\cdot}min^{-1}$)	3.01 ± 0.1[*]	1.93 ± 0.1[*]	4.22 ± 0.1[*]	3.35 ± 0.1[*]	2.69 ± 0.1[*]
Puyau ($kcal{\cdot}min^{-1}$)	1.79 ± 1.1[*]	1.25 ± 0.04[*]	2.39 ± 0.1[*]	1.96 ± 0.1[*]	1.62 ± 0.1[*]
Actical-Predicted Energy Cost (mean± *SE*)					
Heil 1R ($kcal{\cdot}min^{-1}$)	2.88 ± 0.1[*]	1.78 ± 0.1[*]	3.83 ± 0.2	3.25 ± 0.2[*]	2.58 ± 0.1[*]
Heil 2R ($kcal{\cdot}min^{-1}$)	2.68 ± 0.1[*]	1.72 ± 0.1[*]	3.51 ± 0.2	3.02 ± 0.2[*]	2.39 ± 0.1[*]
Puyau ($kcal{\cdot}min^{-1}$)	2.01 ± 0.1[*]	1.17 ± 0.1[*]	2.74 ± 0.2[*]	2.28 ± 0.2[*]	1.79 ± 0.1[*]

The values in bold are not significantly different from the corresponding measured values. Significantly different across

[a] age groups and

[b] gender

[*] Significant difference between measured and estimated value

Table 3

ActiGraph Bias (95% CI); RMSE for Children

	Freedson (MET)		Treuth (MET)		Trost ($kcal \cdot min^{-2}$)		Puyau ($kcal \cdot min^{-2}$)	
	Bias (95% CI)	**RMSE**	**Bias (95% CI)**	**RMSE**	**Bias (95% CI)**	**RMSE**	**Bias (95% CI)**	**RMSE**
Children								
Across All Activities	0.1 (0.0, 0.3)	1.1	−0.2 (−0.3, −0.1)	1.1	−1.6 (−1.7, −1.4)	1.9	−2.2 (−2.4, −2.1)	2.6
Treadmill Activities	0.5 (0.4, 0.7)	1.0	0.1 (0.0, 0.3)	0.7	−1.2 (−1.3, −1.1)	1.4	−2.0 (−2.1, −1.9)	2.1
Activities of Daily Living	−0.2 (−0.4, 0.0)	1.2	−0.4 (−0.6, −0.2)	1.3	−1.8 (−2.0, −1.6)	2.2	−2.4 (−2.6, −2.1)	2.9
3.22 km/hr 0% grade	0.3 (0.1, 0.5)	0.6	0.1 (0.0, 0.3)	0.4	−1.2 (−1.4, −1.1)	1.3	−1.6 (−1.7, −1.5)	1.7
3.22 km/hr 3% grade	0.1 (−0.1, 0.3)	0.5	−0.1 (−0.3, 0.0)	0.5	−1.5 (−1.7, −1.3)	1.6	−2.0 (−2.1, −1.9)	2.0
4.83 km/hr 0% grade	1.0 (0.7, 1.2)	1.2	0.4 (0.2, 0.6)	0.8	−1.0 (−1.2, −0.8)	1.1	−2.1 (−2.2, −1.9)	2.1
5.63 km/hr 0% grade	0.9 (0.4, 1.3)	1.4	0.2 (−0.2, 0.6)	1.0	−1.2 (−1.5, −0.9)	1.5	−2.5 (−2.7, −2.3)	2.5
Backpack (4.5 kg)	1.0 (0.8, 1.3)	1.2	0.5 (0.3, 0.7)	0.8	−0.9 (−1.1, −0.7)	1.1	−1.9 (−2.0, −1.8)	1.9
Basketball	−0.6 (−0.9, −0.3)	1.0	−1.5 (−1.8, −1.2)	1.7	−3.0 (−3.3, −2.8)	3.1	−4.6 (5.0, −4.3)	4.7
Bike	−1.9 (−2.3, −1.6)	2.1	−1.9 (−2.2, −1.6)	2.1	−3.3 (−3.6, −3.0)	3.4	−3.4 (−3.9, −3.0)	3.6
Crafts	0.4 (0.3, 0.5)	0.5	0.5 (0.5, 0.6)	0.6	−0.8 (−0.9, −0.6)	0.9	−0.8 (−0.9, −0.7)	0.8
Wii Tennis	−0.1 (−0.2, 0.1)	0.4	0.0 (−0.2, 0.1)	0.4	−1.4 (−1.6, −1.2)	1.5	−1.5 (−1.7, −1.3)	1.6

CI = Confidence Interval; RMSE = Root Mean Squared Error; km/hr = kilometers per hour; m = meters; sec = seconds; gr = grade. The values in bold indicate accurate estimates.

Table 4

ActiGraph Bias (95% CI); RMSE for Adolescents

	Freedson (MET)		Treuth (MET)		Trost ($kcal \cdot min^{-2}$)		Puyau ($kcal \cdot min^{-2}$)	
	Bias (95% CI)	**RMSE**	**Bias (95% CI)**	**RMSE**	**Bias (95% CI)**	**RMSE**	**Bias (95% CI)**	**RMSE**
			Adolescents					
Across All Activities	−0.4 (−0.6, −0.2)	1.5	−0.2 (−0.4, 0.0)	1.4	−0.9 (−1.1, −0.7)	2.0	−2.7 (−3.0, −2.5)	3.3
Treadmill Activities	0.0 (−0.2, 0.3)	1.3	0.1 (−0.1, 0.3)	1.2	−0.8 (−1.0, −0.6)	1.4	−2.9 (−3.2,—2.7)	3.2
Activities of Daily Living	−0.7 (−1.0, −0.5)	1.6	−0.4 (−0.7, −0.2)	1.5	−1.0 (−1.3, −0.6)	2.3	−2.6 (−2.9, −2.2)	3.4
4.83 km/hr 0% grade	0.3 (0.0, 0.7)	0.9	0.5 (0.2, 0.8)	1.0	0.1 (−0.2, 0.4)	0.8	−1.8 (−2.0, −1.6)	1.9
5.63 km/hr 0% grade	0.4 (0.0, 0.8)	1.1	0.5 (0.1, 0.8)	1.1	−0.2 (−0.5, 0.2)	0.9	−2.2 (−2.4, −1.9)	2.3
5.63 km/hr 3% grade	−0.5 (−0.9, 0.0)	1.3	−0.4 (−0.9, 0.0)	1.3	−1.2 (−1.5, −0.9)	1.4	−3.3 (−3.5, −3.0)	3.3
8.05 km/hr 0% grade	−0.1 (−0.7, 0.6)	1.7	−0.3 (−0.9, 0.3)	1.5	−2.1 (−2.4, −1.7)	2.2	−4.8 (−5.1, −4.4)	4.8
Backpack (6.8 kg)	0.6 (0.3, 0.9)	1.0	0.7 (0.5, 1.0)	1.0	0.4 (0.1, 0.6)	0.8	−1.6 (−1.8, −1.4)	1.7
Basketball	−1.9 (−2.4, −1.4)	2.4	−2.0 (−2.5, −1.5)	2.4	−3.6 (−4.3, −2.9)	4.1	−5.9 (−6.7, −5.1)	6.3
Bike	−2.2 (−2.6, −1.9)	2.4	−1.8 (−2.1, −1.5)	2.0	−2.4 (−2.9, −1.8)	2.7	−3.6 (−4.2, −3.1)	3.9
Board games	0.2 (0.1, 0.4)	0.4	0.7 (0.6, 0.8)	0.8	0.7 (0.4, 1.0)	1.1	−0.5 (−0.7, −0.4)	0.7
Wii Tennis	−0.3 (−0.5, −0.2)	0.5	0.1 (0.0, 0.3)	0.4	0.1 (−0.2, 0.4)	0.8	−1.2 (−1.4, −1.0)	1.3

CI = Confidence Interval; RMSE = Root Mean Squared Error; km/hr = kilometers per hour; m = meters; sec = seconds; gr = grade. The values in bold indicate accurate estimates.

Table 5

Actical Bias (95% CI); RMSE for Children

	Heil 1R (kcal·min^{-1})		Heil 2R (kcal·min^{-1})		Puyau (kcal·min^{-1})	
	Bias (95% CI)	**RMSE**	**Bias (95% CI)**	**RMSE**	**Bias (95% CI)**	**RMSE**
			Children			
Across All Activities	−1.6 (−1.7, −1.4)	1.9	−1.6 (−1.8, −1.5)	2.0	−2.2 (−2.3, −2.1)	2.4
Treadmill Activities	−1.3 (−1.4, −1.2)	1.3	−1.2 (−1.3, −1.2)	1.3	−1.8 (−1.9, −1.7)	1.8
Activities of Daily Living	−1.8 (−2.0, −1.6)	2.3	−1.9 (−2.2, −1.7)	2.4	−2.5 (−2.7, −2.3)	2.8
3.22 km/hr 0% grade	−1.1 (−1.2, −1.1)	1.1	−0.9 (−1.0, −0.8)	1.0	−1.7 (−1.8, −1.6)	1.7
3.22 km/hr 3% grade	−1.5 (−1.6, −1.4)	1.5	−1.3 (−1.4, −1.2)	1.4	−2.1 (−2.2, −2.0)	2.1
2.5 mph 0% grade	−1.2 (−1.3, −1.1)	1.3	−1.3 (−1.4, −1.2)	1.3	−1.6 (−1.7, −1.5)	1.6
4.83 km/hr 0% grade	−1.3 (−1.5, −1.2)	1.4	−1.5 (−1.6, −1.3)	1.5	−1.7 (−1.9, −1.6)	1.8
Backpack (4.5 kg)	−1.3 (−1.4, −1.2)	1.4	−0.8 (−1.0, −0.5)	1.1	−1.8 (−1.9, −1.6)	1.8
Basketball	−3.7 (−4.0, −3.4)	3.8	−3.7 (−4.1, −3.4)	3.9	−4.1 (−4.4, −3.8)	4.2
Bike	−2.8 (−3.2, −2.4)	3.0	−3.2 (−3.6, −2.8)	3.4	−3.7 (−4.1, −3.3)	3.8
Crafts	−0.2 (−0.3, −0.2)	0.3	−0.8 (−0.9, −0.7)	0.8	−1.2 (−1.3, −1.1)	1.3
Wii Tennis	−0.9 (−1.0, −0.7)	0.9	−1.3 (−1.4, −1.1)	1.3	−1.7–1.8, −1.6)	1.8

CI = Confidence Interval; RMSE = Root Mean Squared Error; km/hr = kilometers per hour; gr = grade. The values in bold indicate accurate estimates.

Table 6

Actical Bias (95% CI); RMSE for Adolescents

	Heil 1R (kcal·min^{-1})		Heil 2R (kcal·min^{-1})		Puyau (kcal·min^{-1})	
	Bias (95% CI)	**RMSE**	**Bias (95% CI)**	**RMSE**	**Bias (95% CI)**	**RMSE**
Adolescents						
Across All Activities	−1.3 (−1.5, −1.1)	2.2	−1.6 (−1.8, −1.4)	2.4	−2.4 (−2.6, −2.2)	2.9
Treadmill Activities	−0.9 (−1.1, −0.7)	1.4	−1.1 (−1.3, −0.9)	1.5	−1.8 (−1.9, −1.6)	1.9
Activities of Daily Living	−1.6 (−1.9, −1.2)	2.6	−2.0 (−2.4, −1.6)	3.0	−2.8 (−3.2, −2.5)	3.4
2.5 mph 0% grade	−0.7 (−0.9, −0.5)	0.9	−0.6 (−0.9, −0.4)	0.9	−1.4 (−1.5, −1.2)	1.4
4.83 km/hr 0% grade	−0.8 (−1.0, −0.5)	1.0	−0.9 (−1.2, −0.7)	1.1	−1.4 (−1.6, −1.1)	1.5
4.83 km/hr 3% grade	−2.1 (−2.2, −1.9)	2.1	−2.2 (−2.4, −2.1)	2.3	−2.7 (−2.9, −2.5)	2.7
8.05 km/hr 0% grade	0.2 (−0.3, 0.6)	1.0	−0.6 (−0.9, −0.2)	1.1	−1.7 (−2.0, −1.4)	1.8
Backpack (6.8 kg)	−0.8 (−1.0, −0.6)	0.9	0.1 (−0.4, 0.6)	1.4	−1.5 (−1.7, −1.3)	1.6
Basketball	−4.7 (−5.4, −3.9)	5.1	−4.8 (−5.7, −4.0)	5.3	−5.4 (−6.2, −4.6)	5.8
Bike	−2.5 (−2.8, −2.1)	2.7	−3.4 (−3.8, −3.0)	3.5	−4.1 (−4.5, −3.7)	4.2
Board games	0.3 (0.1, 0.5)	0.6	−0.7 (−0.9, −0.5)	0.8	−1.4 (−1.6, −1.3)	1.5
Wii Tennis	−0.3 (−0.5, −0.1)	0.6	−1.2 (−1.4, −1.1)	1.3	−1.9 (−2.1, −1.7)	2.0

CI = Confidence Interval; RMSE = Root Mean Squared Error; km/hr = kilometers per hour; gr = grade. The values in bold indicate accurate estimates.

Table 7

Agreements Between Actual and Predicted Intensity Classifications

Groups	Kappa (% Agreement)	Kappa (95% CI)
Actigraph Equations		
Light Intensity		
Freedson	0.40 (68.3)	0.33–0.46
Treuth	0.34 (64.42)	0.28–0.41
Trost	0.22 (77.7)	0.12–0.32
Puyau	0.16 (54.3)	0.11–0.21
Moderate Intensity		
Freedson	0.15 (57.3)	0.07–0.23
Treuth	0.09 (54.62)	0.01–0.18
Trost	0.34 (68.1)	0.26–0.43
Puyau	−0.009 (43.1)	−0.09–0.07
Vigorous Intensity		
Freedson	0.32 (83.3)	0.22–0.41
Treuth	0.25 (82.1)	0.16–0.34
Trost	0.55 (88.3)	0.46–0.65
Puyau	0.03 (81.7)	−0.01–0.08
Actical Equations		
Light Intensity		
Puyau	−0.01 (79.7)	−0.09–0.07
Heil 1R	0.32 (80.4)	0.22–0.42
Heil 2R	0.32 (80.3)	0.22–0.42
Moderate Intensity		
Puyau	0.14 (54.6)	0.07–0.21
Heil 1R	0.26 (61.5)	0.18–0.33
Heil 2R	0.25 (60.9)	0.17–0.32
Vigorous Intensity		
Puyau	0.27 (84.8)	0.17–0.37
Heil 1R	0.34 (85.8)	0.23–0.44
Heil 2R	0.31 (85.2)	0.20–0.41