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Estimating Physical Activity in Youth Using an Ankle Accelerometer

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Abstract

This study developed and validated a vector magnitude (VM) two-regression model (2RM) for use with an ankle-worn ActiGraph accelerometer. For model development, 181 youth (mean ± SD; age, 12.0 ± 1.5 yr) completed 30 min of supine rest and 2–7 structured activities. For cross-validation, 42 youth (age, 12.6 ± 0.8 yr) completed approximately 2 hr of unstructured physical activity (PA). PA data were collected using an ActiGraph accelerometer, (non-dominant ankle) and the VM was expressed as counts/5-s. Measured energy expenditure (Cosmed $K4b^2$) was converted to youth METs (MET_y; activity VO_2 divided by resting VO_2). A coefficient of variation (CV) was calculated for each activity to distinguish continuous walking/running from intermittent activity. The ankle VM sedentary behavior threshold was ≤10 counts/5-s, and a CV≤15 counts/5-s was used to identify walking/running. The ankle VM2RM was within 0.42 MET_y of measured MET_y during the unstructured PA (P>0.05). The ankle VM2RM was within 5.7 min of measured time spent in sedentary, LPA, MPA, and VPA (P>0.05). Compared to the $K4b^2$, the ankle VM2RM provided similar estimates to measured values during unstructured play and provides a feasible wear location for future studies.

Keywords

motion sensor; energy expenditure; activity counts variability; children; adolescents

INTRODUCTION

Although the benefits of physical activity (PA) participation in children are well established, more accurate measures of PA are needed in order to refine our understanding of the positive influence of PA on child health outcomes. Objective monitors including accelerometers are a preferred method of assessing habitual PA as they can estimate energy expenditure (EE) and time spent in PA intensities. However, the choice of placement site can impact wear

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compliance and precision of the prediction algorithm. Currently, there is not an optimal placement location that maximizes both compliance and precision.

The hip is the most common site for objective measurement of PA using accelerometers (Montoye, Moore, Bowles, Korycinski, & Pfeiffer, 2016), but recently there has been increased interest in the use of alternative sites (e.g. wrist). For example, the National Health and Nutrition Examination Survey (NHANES) 2011–2014 (Troiano, McClain, Brychta, & Chen, 2014) and the UK Biobank study (Sudlow et al., 2015) used the wrist location. The ankle is one location that has potential for obtaining valid estimates of PA using accelerometers, but there are limited studies on that use the ankle as an accelerometer placement site. In adults, there are conflicting reports with some studies showing that the use of an accelerometer worn on the ankle has a lower relationship with EE (Leenders, Nelson, & Sherman, 2003; Melanson & Freedson, 1995) and lower activity classification accuracy (de Vries, Engels, & Garre, 2011) than a hip-worn device. However, other studies have shown that the use of the ankle location was similar to or better than the hip or wrist location for estimating EE in adults (Heil, 2006; Hibbing, LaMunion, Kaplan, & Crouter, 2017; Kim, Jung, Park, & Joo, 2014) and youth (Heil, 2006). While there are conflicting results for the use of ankle worn accelerometers for predicting EE, the pedometer literature shows that the StepWatch, which is an ankle worn device, is the most accurate device for step counting (Bassett, Toth, LaMunion, & Crouter, 2017).

Use of the ankle as a wear location allows for the use of 24-hr wear protocols that should increase wear compliance, since the participant does not need to remove the device during sleep. The International Study of Childhood Obesity, Lifestyle and the Environment (ISCOLE) successfully used a 24-hr wear protocol using a waist-worn accelerometer and had a mean waking wear time of 14.8 hr/d and more than 22 hr/d of total wear time in a sample of 6539 children from 12 countries (Katzmarzyk et al., 2015). Specifically, in the U.S. ISCOLE participants, 491 of the 640 participants (76.7%) had valid data, with an average of 6.4 valid days and 1357 minutes of wear time per day (Tudor-Locke et al., 2015). In comparison, NHANES 2003–2006, which used a hip worn accelerometer, had valid data across the same age range in 618 of 987 participants (62.6%), and on average had 61.8 fewer minutes of waking wear time than U.S. ISCOLE participants (Tudor-Locke et al., 2015). Hager and colleagues (Hager et al., 2015) used an ankle-worn Actical accelerometer for a 7-day free-living measurement in adolescent girls, using a 24-hr wear protocol and showed the Actical device to be valid, reliable, and feasible for use on the ankle in adolescent females. Of primary importance was that during the 7-day free-living measurement, 99.6% of the 459 eligible participants agreed to wear the Actical and 386 (84.1%) had valid data at the end of the 7-day measurement, with an average wear time of approximately 1437 min/d. The primary reasons for missing data were: improper programming (n=24, 5.2%), device malfunction (n=11, 2.4%), lost device or not returned (n=23, 5%), or wore the Actical for less than two days (n=13, 2.8%). Based on the available evidence the use of a 24-hr wear protocol appears to increase both compliance and wear time, which is especially important in youth, where there tends to be less compliance with wearing hip worn devices.

Previously, we developed a two-regression model (2RM), using an ActiGraph worn on the hip, for use in adults (Crouter, Clowers, & Bassett, 2006; Crouter, Kuffel, Haas, Frongillo, &

Bassett, 2010) and youth (Crouter, Horton, & Bassett, 2012, 2013). The 2RM is able to discriminate between continuous walking/running and intermittent lifestyle activities based on the variability in accelerometer counts. Given the potential for excellent wear compliance and the paucity of studies using accelerometers on the ankle, there is a need to develop and validate methods of estimating EE and time spent in PA intensities in youth across a wide range of activities. Therefore, the purpose of this study was to develop a new vector magnitude 2RM (VM2RM) for youth, using an ankle worn ActiGraph GT3X accelerometer. The second purpose of the study was to examine the validity of the newly developed 2RM during unstructured PA.

METHODS

Participants.

Eighty-four girls and 97 boys (8 to 15 years of age) volunteered to participate in the study. The procedures were reviewed and approved by the University of Massachusetts Boston and Boston Public School Institutional Review Board before the start of the study. A parent/legal guardian of each participant signed a written informed consent and filled out a health history questionnaire, and each child signed a written assent prior to participation in the study. Participant exclusion criteria included if the child had any contraindications to exercise, or was physically unable to complete the activities. No participants included in the study were taking medications that would affect their metabolism (*e.g.* Concerta or Ritalin).

Procedures.

This study was part of two previous studies using the same participants and exercise protocols that were combined for the purpose of this study and the methods have been previously reported (Crouter, Flynn, & Bassett, 2015; Crouter et al., 2012, 2013). Specifically, participants recruited for structured activity routines one through three (see below) were part of the first study (Crouter et al., 2012) and participants recruited for structured activity routine four and the unstructured activity (simulated free-living) were part of a second study (Crouter et al., 2013). For development of the ankle prediction models the structured activities from both studies were used and the unstructured PA was used to examine the validity of the developed prediction models. Thus, the participants that completed the structured routine 4 were included in both the development and cross-validation if they completed both parts. All testing took place at GoKids Boston: Research, Training, and Outreach Center, located on the campus of the University of Massachusetts Boston or at a Boston public school.

Structured Activity Routines.

The structured activity routines (n=181) were performed over a 2-day period with a minimum of 24 hours and a maximum of two weeks between testing days. On day 1, participants had their anthropometric measurements taken and they completed 30 minutes of supine rest in a quiet room for an estimate of resting metabolic rate (RMR). On day 2, participants completed structured PA that was broken into four routines. All youth who participated in the study had their RMR measured and completed one of the structured PA routines. Each structured activity was performed for eight minutes, with a 1- to 2-minute break between each activity. Routine one (n=38, 45% boys) included: reading, sweeping, Nintendo Wii, Floor Light Space, slow track walking (self-selected speed), and brisk track walking (self-selected speed). Routine two (n=37, 57% boys) included: watching television, Wall Light Space, Dance Dance Revolution, playing catch, track walking with a backpack (self-selected speed), and soccer around cones. Routine three (n=37, 57% boys) included: searching internet, vacuuming, Sport Wall, Trazer, workout video, track running (self-selected speed). Routine four (n=69, 55% boys) included: computer games, board games, light cleaning, Jackie Chan video game, wall ball, walking a course around campus (self-selected speed), and running a course around campus (self-selected speed). For each routine, activities were performed in the order listed above and a detailed description of these activities can be found elsewhere (Crouter et al., 2012, 2013). Due to scheduling issues, participants in routine four, completed between 2–7 activities.

Indirect calorimetry (Cosmed K4b^2, Rome Italy) was used to measure oxygen consumption (VO_2) during all testing. Simultaneously, activity data were collected using an ActiGraph GT3X (routines 1–3) or ActiGraph GT3X+ (routine 4) accelerometer positioned on the non-dominant ankle above the lateral malleolus. For weight bearing activities, 2 kg were added to the participant's body weight to account for the additional weight of the devices.

Unstructured PA Measurement.

Participants who completed routine four were asked to return for a third day of testing which consisted of approximately two hours of unstructured PA (n=42). The unstructured PA testing was designed to simulate free-living activity. During the unstructured PA measurement, a research assistant was with the child at all times, but did not communicate with the child or instruct them what to do. If water and bathroom breaks were needed, the Cosmed mask was removed, resulting in a loss of data and these time periods were later removed from the analysis. All testing took place at the University of Massachusetts Boston, or at the school the youth attended. During the measurement period, participants were allowed to interact with other youth who were not part of the testing, which allowed for a more naturalistic setting. During the unstructured PA session, a range of activities were performed including: sedentary behaviors (e.g., watching movies, reading, homework), active games (e.g., Dance Dance Revolution and Nintendo Wii), and recreational activities (e.g., soccer, basketball, lifting weights) (for further detail see Crouter et al. (2013)). Oxygen consumption and activity data (GT3X+) were collected in the same manner as described above for the structured activities.

Anthropometric measurements.

Participants had their height and weight measured in light clothing and without shoes, using a stadiometer and a physician's scale, respectively. Body mass index (BMI; body mass (kg) divided by height squared (m^2)) was calculated and gender- and age-specific BMI percentiles were calculated using CDC algorithms (Centers for Disease Control and Prevention (CDC), 2014).

Indirect calorimetry.

The Cosmed K4b^2 was used to measure oxygen consumption and carbon dioxide production during each structured PA routine and unstructured PA measurement. Prior to each test the oxygen and carbon dioxide analyzers were calibrated according to the manufacturer's instructions.

ActiGraph accelerometer.

The ActiGraph GT3X (3.8 × 3.7 × 1.8 cm; 27 grams) and ActiGraph GT3X+ (4.6 × 3.3 × 1.5 cm; 19 grams) tri-axial accelerometers were used for activity measurement. The GT3X was used in the first study (structured activity routines 1–3) and prior to starting the second study (structured routine 4 and unstructured PA) the GT3X+ was released and was used for the second study. The GT3X and GT3X+ were initialized using 1-second epochs and 30 Hz, respectively with the low frequency extension turned on and the accelerometer time was synchronized with a digital clock so the start time could be synchronized with the Cosmed K4b^2. At the conclusion of the test the accelerometer data were downloaded for subsequent analysis. During all testing the GT3X or GT3X+ was positioned on the ankle just proximal to the lateral malleolus on the same side of the body as their dominant hand (defined as which hand they write with). In addition, the accelerometer was positioned so that the vertical axis (VA) of the ActiGraph was parallel to the vertical axis of the leg.

Data analysis.

The breath-by-breath data collected using the Cosmed K4b^2 were averaged over a 1-minute period for the structured activities (routine 1–4) and a 15-sec period for the unstructured PA. VO_2 (ml·min^{-1}) data were converted to VO_2 (ml·kg^{-1}·min^{-1}). To account for higher resting metabolic rates in youth compared to adults (Malina, Bouchard, & Bar-Or, 2004; Schofield, 1985) youth-METs (MET_y) were calculated by dividing the VO_2 (ml·kg^{-1}·min^{-1}) for each by the participant's supine resting VO_2 (ml·kg^{-1}·min^{-1}). For each structured activity, the MET_y values for minutes 4 to 7 were averaged and used for the subsequent analysis. The entire unstructured PA measurement period was used, for cross validation, with the exception of times when the Cosmed K4b^2 mask was removed for water or bathroom breaks. The mean MET_y across valid minutes of the unstructured PA was used to represent the measured MET_y value. To classify PA intensity, the MET_y value for each minute of the unstructured PA was used to classify the minute as sedentary behavior (<1.5 MET_y), light PA (LPA, 1.5–2.9 MET_y), moderate PA (MPA, 3.0–5.99 MET_y) or vigorous PA (VPA, ≥6.0 MET_y). Each intensity category was summed to obtain the total minutes. Moderate-to-vigorous PA (MVPA, ≥3.0 MET_y), was obtained by combing the MPA and VPA minutes.

The 1-sec count data (GT3X) and raw acceleration data (GT3X+) for the VM (square root of the sum squared activity counts from each axis) was converted to counts per 5 seconds. For the development of the 2-regression model (2RM) a coefficient of variation (CV) was also calculated. Following the methods we previously used in adults (Crouter et al., 2010) and youth (Crouter et al., 2012), a CV was calculated for each 5-s epoch by examining each 5-s epoch and all combinations of the surrounding 11 5-sec epochs. For example, the 5-s epoch of interest and: 1) the 11 5-s epochs before, 2) the 10 5-s epochs before and one 5-s epoch after, and 3) the nine 5-s epochs before and two 5-s epochs after. This process was carried out until all combinations were examined and the lowest CV from the 12 possible conditions was used as the CV for that 5-s epoch. Examining each 5-s epoch in this manner, allows for the determination of whether a specific 5-sec epoch falls within a continuous walking/running bout of 1-min or if the epoch is part of an intermittent lifestyle activity. The mean counts and CV were calculated for minutes 4–7 of each activity and all minutes of the unstructured activity were used, except for when the mask was removed, to match what was done with the Cosmed data.

Statistical treatment.

All statistical analyses were performed using IBM SPSS version 21.0 for windows (IBM, Armonk, NY). For all analyses, an alpha level of 0.05 was used to indicate statistical significance. All values are reported as mean ± standard deviation.

For the development of prediction models, the data from the structured activities (routines 1–4) were used. Initially, the mean counts and percentile distribution were used to determine an inactivity threshold for sedentary behaviors (e.g., lying, reading, and video watching). Additionally, the mean CV and percentile distribution were used to determine a CV threshold to determine whether a 5-s epoch was part of a continuous walk/run bout or intermittent lifestyle activity. For the VM2RM, the inactivity threshold was first applied, followed by splitting the data based on the CV classification of if the data was determined to be walking/running or intermittent lifestyle. Regression analysis was then used to predict MET_y from the counts per 5-s for the walk/run activities and intermittent lifestyle activities.

Following the VM2RM development, the unstructured PA data were used to validate the model. Paired t-tests were used to compare measured (Cosmed) and predicted MET_y and time spent in sedentary behaviors, LPA, MPA, VPA, and MVPA during the unstructured PA. In addition, measured and predicted MET_y were used to calculate root mean squared error (RMSE; square root of the mean of the squared differences between the prediction and the criterion measure), mean bias, and 95% prediction intervals (95%PI) for the unstructured PA measurement outcomes.

RESULTS

Data for four participants (three who performed structured activities and one who performed unstructured PA) were excluded due to accelerometer malfunction resulting in data loss. Participant descriptive characteristics are shown in table 1. Mean (SD) measured METy values, ankle VM ActiGraph counts per 5 seconds, and number of participants for each structured activity who had valid accelerometer data are shown in table 2.

Development of ActiGraph Ankle Two Regression Model.

The development of the VM2RM included: 1) development of an inactivity threshold, 2) development of a CV threshold, and 3) development of regression equations for continuous walk/run activities and intermittent lifestyle activities. The inactivity thresholds were developed to distinguish sedentary behaviors from LPA. Based on the examination of the mean values and percentile distribution of the sedentary activities (i.e. activities in a lying or sitting position and <1.5 MET_y) the inactivity threshold for the ankle VM was 10 counts per

5 sec. Thus, when the counts per 5 sec are below the inactivity threshold the individual is credited with 1.0 MET_y. Next, using only the data above the proposed inactivity threshold, a CV threshold of 15 was determined to distinguish continuous walking and running from intermittent lifestyle activities for the VM. Therefore, when the CV is below the threshold the activity is classified to be continuous walking and running.

To develop the regression equations the data were separated based on whether they were classified as continuous walk/run (CV≤15) or intermittent lifestyle activity (CV>15). Separate regression lines relating the VM counts per 5 sec to EE (MET_y) were then developed for each CV group. The VM2RM to predict gross EE (MET_y) from the ActiGraph ankle VM counts consists of three parts (inactivity threshold and two separate regression models):

Youth VM2RM for the ankle:

(1) if the VM counts per 5 sec are ≥ 10, energy expenditure = 1.0 MET_y,

(2) if the VM counts per 10 sec are > 10

- **a.** and the CV of the VM counts per 5 sec ≤ 15, then energy expenditure (MET_y) = 0.137 + (0.0036*ActiGraph VM counts per 5 s)) (R^2 = 0.404; SEE = 1.760),

- **b.** or the CV of the VM counts per 5 sec are > 15, then energy expenditure (MET_y) = 1.627 + (0.0043 * ActiGraph VM counts per 5 s) (R^2 = 0.535; SEE = 1.341)

(3) Once a MET_y value has been calculated for each 5-s epoch within a minute on the ActiGraph clock, the average MET_y value of 12 consecutive 5-s epochs within each minute is calculated to obtain the average MET_y value for that minute.

Validation Study to Examine the ActiGraph Two-Regression Models during Unstructured PA.

On average, children were monitored for 95.0 ± 36.5 min (range, 25–130 minutes) during the unstructured PA measurement period. Table 3 shows the RMSE, MAPE, and mean bias and 95%PI for MET_y and time spent in sedentary behaviors, LPA, MPA, VPA, and MVPA during the unstructured PA measurement. Figure 1 shows the mean measured and predicted time spent in sedentary behaviors, LPA, MPA, and VPA during the unstructured PA measurement. There was no difference between the mean measured MET_y (3.35±2.13) and predicted VM2RM MET_y (2.94±1.20; P>0.05); however, there were large individual errors, with the 95% PI ranging from −2.15 to 2.99 MET_y. The VM2RM was not significantly different from measured time spent in sedentary behaviors, LPA, MPA or VPA (P>0.05) and had mean biases that ranged from 10–39%. For MVPA, the VM2RM was within 2% of measured MVPA (P>0.05).

DISCUSSION

The primary purpose of this study was to develop and validate a youth VM2RM for the ankle that utilizes the ActiGraph GT3X accelerometer. Using a separate sample performing unstructured free-living activities, the VM2RM for the ankle was not significantly different from measured MET_y or measured time spent in sedentary behaviors and LPA, MPA, and VPA.

Although the hip is the most widely used accelerometer placement site, it is important to explore alternative sites as public health interventions aim to increase wear time compliance and accurate predictions of EE. Previous studies have explored the use of the ankle site in adults (Heil, 2006; Hibbing et al., 2017; Kim et al., 2014; Leenders et al., 2003; Melanson & Freedson, 1995) and youth (de Vries et al., 2011; Hager et al., 2015; Heil, 2006) and have shown conflicting results. de Vries et al. (2011), using the ActiGraph accelerometer, showed that the hip, compared to the ankle, was more accurate for predicting PA type using artificial neural networks. In contrast, Heil (2006) showed that with the Actical the ankle was not different from the wrist or hip for prediction of EE. Additionally, Hager and colleagues (Hager et al., 2015) also showed the Actical device to be valid, reliable, and feasible for use on the ankle in adolescent females with less than 3% of participants (N=459) wearing the Actical for less than three days during a 7 day measurement period.

While the current study did not compare the results of the ankle location directly to other placement sites, we can draw some comparisons with previously developed models for the hip and wrist locations. Using the same data set used for development of the ankle models, our group has developed regression models for the hip (Crouter et al., 2012, 2013) and dominant wrist (Crouter et al., 2015) locations. In our previous work using the same unstructured PA data set for validation of the hip and wrist models we found the VM2RM hip model and a VM single regression wrist model to have to have a RMSE of 1.50 and 1.38, respectively, compared to a RMSE for the VM2RM ankle model of 1.34 (figure 2). In addition, when examining the mean bias (measured minus predicted) and 95% PI, the ankle model has a similar mean bias for prediction of MET_y and time spent in sedentary behaviors, LPA, MPA, VPA, and MVPA compared to the hip VM2RM and wrist VM single regression model. However, the individual error for the ankle VM2RM is the same or lower for most estimates suggesting that using the ankle location will also reduce the individual error compared to using models developed for other locations.

It should be noted that newer models using machine learning algorithms have resulted in lower RMSE for prediction of MET_y than what has been found in the current study. For example, Trost et al. (Trost, Wong, Pfeiffer, & Zheng, 2012), used an artificial neural network for estimating MET_y in youth wearing an ActiGraph GT1M while performing 12 structured activities and found a RMSE of 0.9 MET_y. In contrast, Mu et al. (Mu, Lo, Ding, Amaral, & Crouter, 2014) compared several machine learning approaches, including Bipart and an artificial neural network, for predicting MET_y in youth wearing an ActiGraph GT3X while performing 18 structured activities and found a RMSE of 1.37 MET_y and 1.39 MET_y. However, these machine learning models have not been evaluated in youth in a free-living setting where all models typically perform worse than in a lab-based setting so it is unclear if using machine learning approaches are superior for decreasing group estimates in individual error when predicting MET_y with accelerometers. At this time, there does not appear to be a superior model or wear location for predicting PA outcomes with an accelerometer. Based on the results from this and other studies, it appears that the three sites (ankle, wrist, and hip) have similar mean group errors for estimating time spent in PA intensity categories and MET_y, but use of the ankle location may reduce the individual errors. In addition, given the decreased compliance with a hip worn device (Tudor-Locke et al., 2015) and based on evidence from Hager and colleagues (Hager et al., 2015) and the use of a 24-hr protocol in ISCOLE (Katzmarzyk et al., 2015; Tudor-Locke et al., 2015), use of the ankle location may result in increased wear time compliance, resulting in better overall estimates of PA.

To our knowledge, this is the first study to examine the validity of ActiGraph ankle prediction models, developed for youth, in an unstructured, simulated free-living environment. The study has a number of strengths. Indirect calorimety was used for measured EE during both the development (structured activities) and validation (unstructured PA). Secondly, the study includes a large sample of children and adolescents with a broad range of BMI, race/ethnicity, and PA levels. Therefore, the developed prediction models can be applied to other studies that include a diverse group of youth. There were limitations to the study, as well. One limitation was the small number of vigorous activities during both the model development and validation.

In conclusion, this study demonstrates the feasibility of using an ankle-worn ActiGraph device for measuring PA in youth. The VM2RM provided similar estimates to measured MET_y values, and the VM2RM was not significantly different from measured time spent in sedentary behaviors, LPA, MPA, or VPA. Further work is needed to explore wear compliance when using the ankle location.

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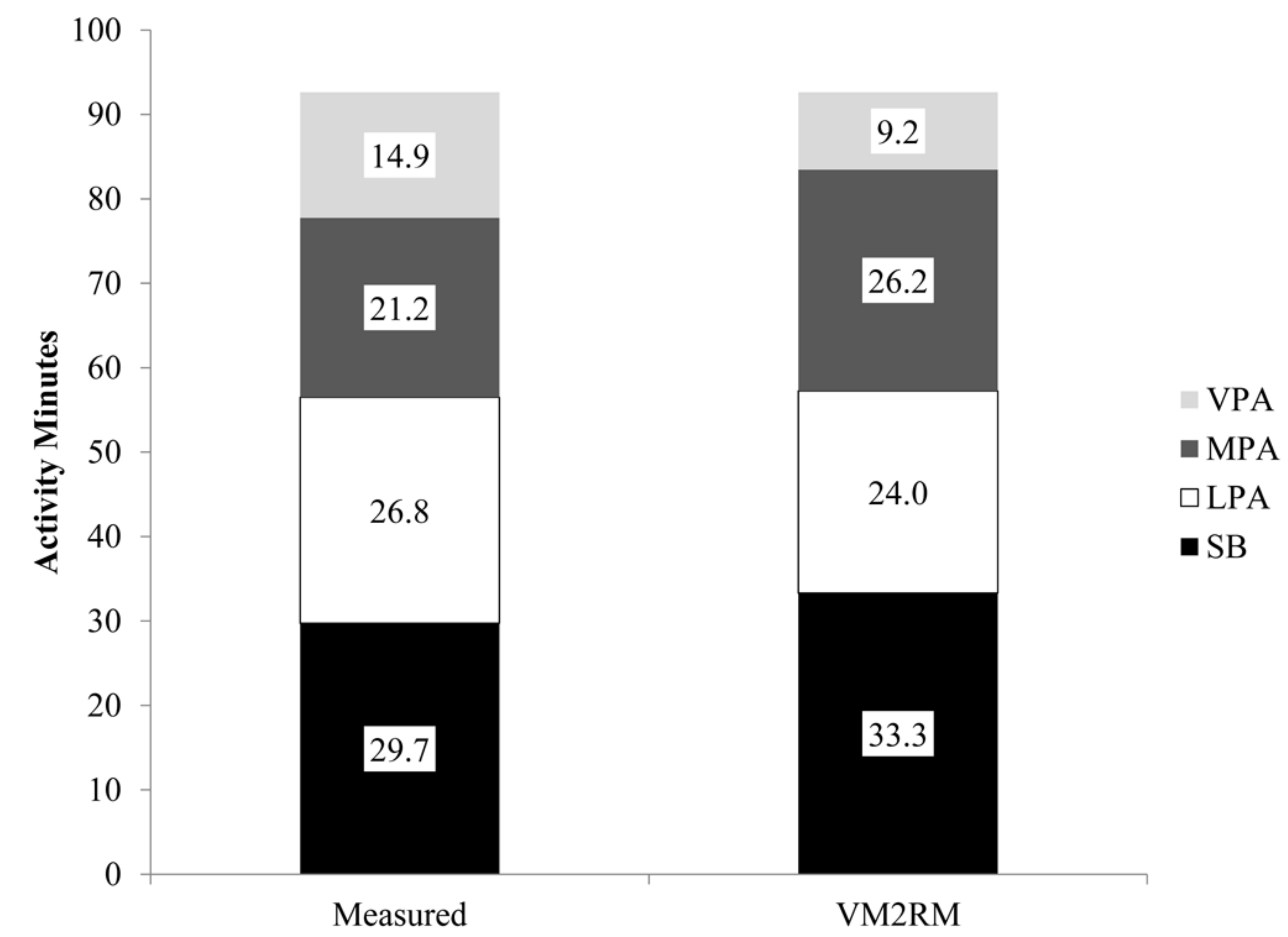

Figure 1.
Distribution of average time spent in sedentary behaviors (SB), light physical activity (LPA), moderate physical activity (MPA) and vigorous physical activity (VPA) during the unstructured PA measurement period for the Cosmed K4b^2 (Measured) and the vector magnitude two-regression model (VM2RM).

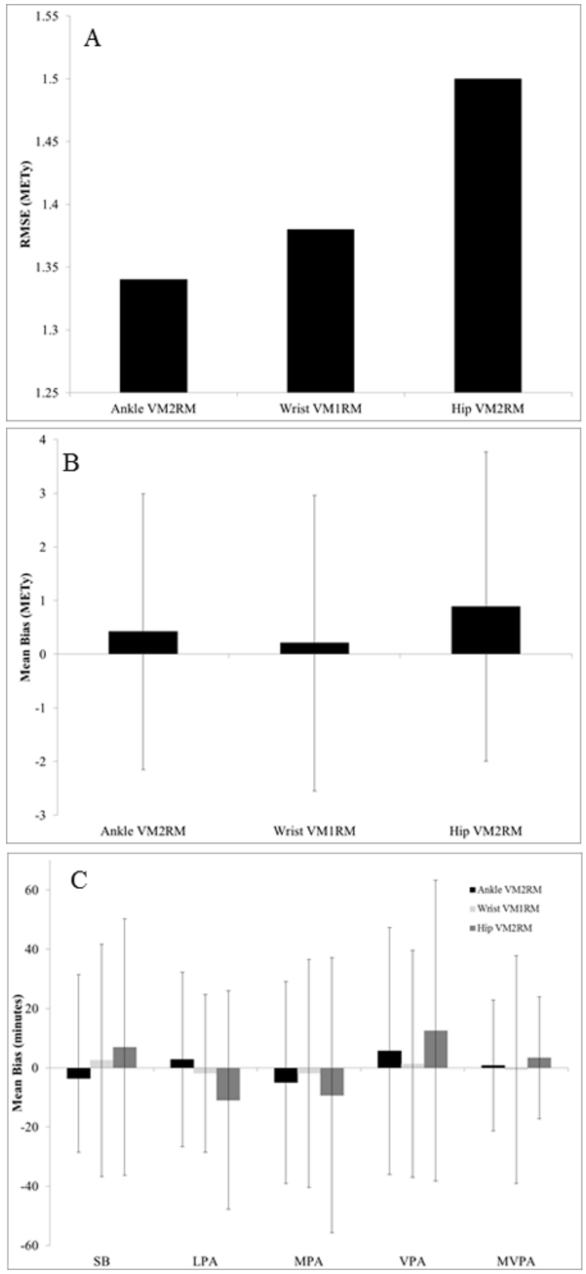

Figure 2.

Group and individual errors for estimates of youth MET (MET_y) and time spent in sedentary behaviors (SB), light physical activity (LPA), moderate physical activity (MPA), vigorous physical activity (VPA), and moderate-to-vigorous physical activity (MVPA), during unstructured free living activity, for the ankle vector magnitude 2-regression model (ankle VM2RM; current study), wrist vector magnitude single regression model (wrist VM1RM; Crouter et al. 2015) and hip VM2RM (Crouter et al. 2013). A) Root mean square error (RMSE) for prediction of MET_y, B) mean bias (Cosmed K4b^2 minus prediction) and 95%

prediction interval for estimates of MET_y, C) mean bias (Cosmed K4b^2 minus prediction) and 95% prediction interval for estimates of SB, LPA, MPA, VPA, and MVPA.

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Table 1.

Descriptive characteristics of the participants.

	Structured Physical Activities (n=181)	Free-Living Activity (n=42)
Age (yrs) ± SD (range)	12.0 ± 1.5 (8–15)	12.6 ± 0.8 (11–14)
8–9 yr olds (n (%))	25 (13.8%)	0.0
10–11 yr olds (n (%))	54 (29.8%)	9 (21.4%)
12–13 yr olds (n (%))	90 (49.7%)	32 (76.2%)
14–15 yr olds (n (%))	12 (6.6%)	1 (2.3%)
Height (cm)	152.3 ± 14.5	156.5 ± 10.2
Weight (kg)	52.1 ± 18.2	57.1 ± 16.5
Male (%)	53.6%	64.3%
BMI Classification (%)		
Normal Weight (5th-85th percentile)	57.2%	45.2%
Overweight (85th-95th percentile)	17.8%	26.2%
Obese (≥ 95th percentile)	25.0%	28.6%
Hispanic (%)	33.2%	21.4%
Race (%)		
Black/African American	51.4%	64.2%
Native American/Alaskan	1.2%	0.0%
Asian	12.1%	19.2%
White	35.3%	16.6%

Table 2.

Measured (Cosmed K4b[2]) oxygen consumption (VO_2), MET_y (measured VO_2 for the activity divided by measured resting VO_2), and vector magnitude (VM) counts per 5 seconds from an ankle mounted ActiGraph accelerometer for each structured activity.

Activity	Measured VO_2 ($ml \cdot kg^{-1} \cdot min^{-1}$)	Measured MET_y	ActiGraph VM Ankle (counts per 5 seconds)	
	Mean (± SD)	Mean (± SD)	Mean (± SD)	25th and 75th percentiles
Supine Rest (n=177)	4.9 (1.5)	1.0 (0.0)	19 (30.0)	0.0, 9.5
Watching Television (n=36)	4.9 (1.4)	1.1 (0.3)	24 (31.6)	3.3, 24.3
Searching Internet (n=36)	4.7 (1.3)	1.1 (0.3)	14 (17.3)	0.6, 22.5
Reading (n=38)	4.9 (1.6)	1.1 (0.4)	24 (29.6)	0.9, 13.2
Playing Computer Games (n=42)	6.3 (2.3)	1.4 (0.5)	21 (63.1)	1.3, 11.6
Playing Board Games/Cards (n=42)	6.6 (2.1)	1.4 (0.5)	29 (74.5)	1.1, 13.5
Workout Video (n=36)	10.1 (3.2)	2.2 (0.7)	199 (97.6)	159.3, 257.3
Nintendo Wii (n=38)	11.4 (5.7)	2.4 (1.1)	192 (271.8)	42.1, 230.5
Vacuuming (n=37)	11.6 (3.0)	2.6 (0.6)	306 (104.3)	265.3, 444.6
Sweeping (n=38)	13.0 (6.3)	2.8 (1.1)	349 (151.1)	245.2, 428.9
Light Cleaning (n=42)	13.2 (3.5)	3.0 (1.3)	245 (206.1)	165.6, 266.5
Slow Track Walking (n=38; avg. 74.6 ± 8.6 $m \cdot min^{-1}$)	15.0 (3.2)	3.3 (1.1)	1067 (238.2)	972.3, 1261.4
Dance Dance Revolution (n=37)	15.2 (4.2)	3.3 (1.0)	365 (102.2)	339.1, 431.0
Playing Catch (n=36)	17.1 (5.2)	3.7 (1.1)	437 (219.3)	345.7, 535.8
Walk with 4.5 kg Backpack (n=36; avg. 78.8 ± 13.6 $m \cdot min^{-1}$)	17.0 (4.7)	3.7 (1.2)	1105 (298.2)	912.0, 1350.6
Walking Course (n=61; avg. 71.7 ± 11.8 $m \cdot min^{-1}$)	18.4 (4.8)	4.1 (1.5)	1036 (189.5)	876.9, 1144.5
Brisk Track Walking (n=37; avg. 93.0 ± 11.3 $m \cdot min^{-1}$)	19.6 (3.9)	4.3 (1.4)	1442 (242.9)	1270.4, 1613.2
Trazer (n=36)	19.4 (7.5)	4.4 (1.8)	599 (148.3)	506.3, 710.5
Floor Light Space (n=38)	21.5 (7.0)	4.6 (1.8)	680 (197.6)	533.4, 809.0
Soccer Around Cones (n=37)	21.2 (8.0)	4.6 (2.1)	935 (255.2)	786.3, 1075.8
Jackie Chan (n=42)	21.7 (5.9)	4.7 (1.4)	521 (170.5)	389.6, 657.0
Wall Light Space (n=37)	21.0 (6.1)	4.5 (1.6)	521 (150.1)	436.5, 617.7
Wall Ball (n=42)	22.2 (7.5)	5.0 (2.3)	530 (229.5)	467.0, 669.6
Sport Wall (n=37)	24.2 (8.6)	5.5 (2.2)	1055 (374.1)	800.4, 1292.2

Activity	Measured VO_2 ($ml \cdot kg^{-1} \cdot min^{-1}$)	Measured MET_y	ActiGraph VM Ankle (counts per 5 seconds)	
	Mean (± SD)	**Mean (± SD)**	**Mean (± SD)**	**25^{th} and 75^{th} percentiles**
Track Running (n=36; avg. 121.2 ± 21.2 $m \cdot min^{-1}$)	24.2 (10.6)	5.5 (2.5)	1623 (414.3)	1369.8, 1887.4
Running Course (n=59; avg. 113.1 ± 19.1 $m \cdot min^{-1}$)	31.2 (7.7)	7.0 (2.8)	1719 (329.8)	1469.2, 1960.1

Table 3.

Root mean square error (RMSE), mean absolute percent error (MAPE), and mean bias (measured minus predicted) and lower and upper 95% prediction intervals (95%PI) for MET_y and time spent in sedentary behaviors (SB), light physical activity (LPA), moderate physical activity (MPA), vigorous physical activity (VPA) and moderate and vigorous physical activity (MVPA) during the unstructured PA.

	VM2RM		
	Mean Bias (95%PI)	**RMSE**	**MAPE**
MET_y	0.42 (−2.15, 2.99)	1.34	22.8
SB	−3.6 (−28.5, 31.4)	17.7	220.3
LPA	2.8 (−26.6, 32.2)	14.8	62.0
MPA	−5.0 (−39.0, 29.1)	17.6	169.1
VPA	5.7 (−36.0, 47.4)	21.4	570.7
MVPA	0.8 (−21.3, 22.8)	11.0	140.5

MET_y, metabolic equivalents (measured VO_2 divided by measured lying RMR VO_2); VM2RM, ankle vector magnitude two-regression model.