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Actigraph GT3X: Validation and Determination of Physical Activity Intensity Cut Points

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Key words

- activity monitor
- physical activity intensity
- energy expenditure

Abstract

The aims of this study were: to compare energy expenditure (EE) estimated from the existing GT3X accelerometer equations and EE measured with indirect calorimetry; to define new equations for EE estimation with the GT3X in youth, adults and older people; and to define GT3X vector magnitude (VM) cut points allowing to classify PA intensity in the aforementioned age-groups. The study comprised 31 youth, 31 adults and 35 older people. Participants wore the GT3X (setup: 1-s epoch) over their right hip during 6 conditions of 10-min duration each: resting, treadmill walking/running at 3, 5, 7, and 9 km·h^{-1}, and repeated sit-stands (30 times·min^{-1}). The GT3X proved to be a good tool to predict EE in youth and adults (able to discriminate between the aforementioned conditions), but not in the elderly. We defined the following equations: for all age-groups combined, EE (METs) = 2.7406 + 0.00056·VM activity counts (counts·min^{-1}) − 0.008542·age (years) − 0.01380· body mass (kg); for youth, METs = 1.546618 + 0.000658·VM activity counts (counts·min^{-1}); for adults, METs = 2.8323 + 0.00054·VM activity counts (counts·min^{-1}) − 0.059123·body mass (kg) + 1.4410·gender (women = 1, men = 2); and for the elderly, METs = 2.5878 + 0.00047·VM activity counts (counts·min^{-1}) − 0.6453·gender (women = 1, men = 2). Activity counts derived from the VM yielded a more accurate EE estimation than those derived from the Y-axis. The GT3X represents a step forward in triaxial technology estimating EE. However, age-specific equations must be used to ensure the correct use of this device.

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Bibliography
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Introduction

Accelerometers allow objective assessment of physical activity (PA) in humans [9]. With the growing number of accelerometer models available in the market, there is an increased need to assess the accuracy of the new devices for PA and energy expenditure (EE) determination, i.e., using validation methods like doubly labeled water or indirect calorimetry [7]. For instance, several accelerometers models such as the CSA/7164, the GT1M, the Tritrac, the Caltrac or the Kenz Select have been validated with indirect calorimetry [1, 3, 6, 10, 19, 24, 27, 33]. The validation of accelerometers with indirect calorimetry allows developing mathematical equation models to predict EE with these devices, as well as to define accelerometer-derived PA cut points [9, 12, 14, 34]. The cut point method is commonly used to assess and classify free-living PA behavior in epidemiologic studies. However, cut points differ across accelerometer models and age ranges [11, 17, 18, 25, 39, 40]. It is thus is necessary to develop specific cut points for each model and age range owing to the importance that PA levels have – as an exposure, main outcome or as confounder – in epidemiologic research [9].

In 2009, Actigraph launched a novel triaxial accelerometer, the so-called GT3X. Sasaki et al. [37] recently compared the GT1M and GT3X activity counts during treadmill walking/running activities. Activity counts obtained from the Y-axis were comparable between the 2 models, but not when obtained from the vector magnitude (VM, which is the vector summed value $\sqrt{X^2+Y^2+Z^2}$) Sasaki et al. [37] reported activity cut points from the VM in order to classify PA in young adults (mean age ~27 years). Although there are reports using the GT3X VM for EE determination [20, 21, 37], no previous study has assessed the accuracy of the GT3X or developed GT3X-specific equations for determining EE

across different age-groups using the same protocol/activities, and the same methodology and statistical analysis.
The 3 main aims of this study were: (i) to compare EE estimated from the existing GT3X equations, and EE measured by indirect calorimetry in youth, adults and older people, and (ii) to improve the accuracy of the GT3X for predicting EE, by defining new equations in the same age-groups; and (iii) to develop GT3X VM cut points to classify PA intensity in the aforementioned age groups.

Methods

Subjects

The study was approved by the University's Human Ethics Committee, it was performed according to the declaration of Helsinki and it was in compliance with the Ethical Standards in Sport and Exercise Science Research [22]. All the subjects provided written consent to participate in the study. The subjects comprised:

(i) 31 youth (19 boys, 12 girls) aged 12–16 years (mean ± SD: 14.7 ± 1.0 years; weight: 59.6 ± 8.9 kg; height: 168.2 ± 6.6 cm; body fat, as estimated with bioelectrical impedance (Tanita BC 420SMA Portable Body Composition Monitor): 17.4 ± 7.5 %);
(ii) 31 adults (16 men, 15 women) aged 40–55 years (47.1 ± 3.5 years; weight: 65.0 ± 16.7 kg; height: 168.0 ± 10.0 cm; body fat: 22.4 ± 6.1 %);
(iii) 35 older adults (13 men, 22 women) aged 65–80 years (71.9 ± 5.4 years; weight: 67.8 ± 17.5 kg; height: 160.9 ± 7.69 cm; body fat: 32.7 ± 5.8 %).

Our study design had a statistical power of 80 % to detect a difference between the group mean and a hypothetical mean of 0.65 METs with a significance level (alpha) of 0.05 (2-tailed).
Young people were recruited from the same high school, adults from the same university and from different fitness centers and older adults from different social centers. All subjects were living in the same city. Exclusion criteria were having musculoskeletal or cardiovascular diseases that could hinder PA. Participants were also excluded if they had any other contraindications to exercise or were taking medication altering metabolic rate. All participants completed the Physical Activity Readiness Questionnaire (PAR-Q), with a total of 3 older adults and 2 adults being excluded from the study because they answered yes to one or more questions.

Experimental procedure

3 GT3X units were updated with the 4.1.0 Firmware version. All units were initialized via a computer interface to collect data in 1-s epochs in the 3 axes. Each participant chose randomly one of the GT3X accelerometers, and the unit was positioned securely on the participants' right hip using an elastic belt. 2 researchers checked the position of the monitor before and after each condition (see below). The accelerometer test protocol consisted of 6 conditions (of 10-min duration each) interspersed with 5-min rest periods: (i) resting; (ii) treadmill (Quasar Med 4.0, h/p/cosmos, Nussdorf-Traunstein, Germany) walking at $3\,km \cdot h^{-1}$; (iii) treadmill walking at $5\,km \cdot h^{-1}$; (iv) treadmill walking or running at $7\,km \cdot h^{-1}$; (v) treadmill running at $9\,km \cdot h^{-1}$; and (vi) repeated sit-stands (30 $times \cdot min^{-1}$). For safety reasons, older adults did not perform the treadmill bouts at $\geq 7\,km \cdot h^{-1}$. Oxygen uptake was measured 'breath-by-breath' continuously during each condition using indirect calorimetry (metabolic cart Oxycon Pro, Jaeger-Viasys Healthcare, Hoechberg, Germany). The metabolic cart was calibrated with a known gas mixture (16 % O_2 and 5 % CO_2) and volume prior to testing each subject [8]. One test had to be repeated seven days later due to an error in the security system of the treadmill. Occasional errant breaths (e.g. due to coughing, swallowing or talking) were deleted from the data set when exceeding 3 standard deviations of the mean, the latter being defined as the average of 2 following and 2 preceding sampling intervals [29].

Measurements

The Actigraph GT3X monitor device (Actigraph, Pensacola, FL, USA) is lightweight (27 g), compact (3.8 × 3.7 × 1.8 cm) and has a rechargeable lithium polymer battery [15]. It uses a solid-state tri-axial accelerometer to collect motion data on 3 axes: vertical (Y), horizontal right-left (X) and horizontal front-back axis (Z). The Actigraph output also includes the VM. The GT3X measures and records time-varying accelerations ranging in magnitude from ~0.05 to 2.5 Gs [15]. The accelerometer output is digitized by a 12-bit analog to digital convertor (ADC) at a rate of 30 Hz [15]. Once digitized, the signal passes through a digital filter that band-limits the accelerometer to the frequency range of 0.25–2.5 Hz [15]. Each sample is summed over an 'epoch' and the output of the Actigraph is given in 'counts'. The counts obtained in a given time period are linearly related to the intensity of the subject's PA during this period. There was no missing data due to errors attributable to accelerometers during the recording or downloading process.

Data analyses

Activity counts were obtained by averaging the activity counts of the four central minutes of each axis (X, Y, Z and VM). METs individually defined (VO_2 divided by measured Resting Metabolic Rate) from the indirect calorimetry were obtained in the same manner. To determine the axis effect on each activity, we used a 2-factor [condition (resting, walking at $3\,km \cdot h^{-1}$, walking at $5\,km \cdot h^{-1}$, walking or running at $7\,km \cdot h^{-1}$, running at $9\,km \cdot h^{-1}$, and repeated sit-stands), axis (X, Y, Z, and VM)] ANOVA test. When the assumptions of sphericity were violated, the Greenhouse Geisser correction factor was applied. A Bonferroni test was used post hoc in all pairwise comparisons when a significant result was found.

Study objective (i): to compare EE estimated from the existing GT3X equations, and EE measured by indirect calorimetry

We used a one-factor (EE) repeated-measures ANOVA to compare indirect calorimetry for each activity in each age-group and to analyze differences between activities. We also used a 3-factor [METs (obtained with indirect calorimetry, predicted from the GT3X), age-group (youth, adult, older) and condition (resting, walking at $3\,km \cdot h^{-1}$, walking at $5\,km \cdot h^{-1}$, walking or running at $7\,km \cdot h^{-1}$, running at $9\,km \cdot h^{-1}$, and repeated sit-stands)] ANOVA to compare GT3X-predicted METs and indirect calorimetry-determined METs in each age-group. If significant main effects were found, the Bonferroni test was used post hoc. We determined the degree of agreement (BIAS), standard deviation of BIAS (SD) and 95 % limits of agreement (LOA) between GT3X EE and indirect calorimetry EE using Bland & Altman plots [5].
The accuracy of previously proposed regression equations for EE estimation with the GT3X was determined by examining the BIAS, SD and LOA for each Bland-Altman plot. The equations we studied were: (i) the Work-energy Theorem [15], where EE

(kcal·min^{-1}) = 0.000019 · activity counts (counts·min^{-1}) · body mass (kg); (ii) the combined equation [15] [Work-energy Theorem, where activity counts do not exceed 1952 counts·min^{-1}, and Freedson Equation, where activity counts exceed 1952 counts·min^{-1} (Freedson Equation: EE (kcal·min^{-1}) = 0.00094 activity counts (counts·min^{-1}) + 0.1346 body mass (kg) – 7.37418)]; (iii) and the equation reported by Sasaki et al. [37], where EE (METs) = 0.000863 (VM) + 0.668876.

Study objective (ii) to define new equations to estimate EE with the GT3X in youth, adults and older people

To determine the new equations in each age-group, we used linear regression analysis to predict METs from VM GT3X counts·min^{-1}. The accuracy of the new proposed equations was examined by calculating the BIAS, SD and LOA for each Bland-Altman plot. A leave-one-out cross validation was performed for assessing if the equations could be generalized to an independent data set. Finally, the association between the difference and the magnitude of the measurement (i.e., heteroscedasticity) was examined by regression analysis, entering the difference between the EE measured and the EE estimated using the EE (METs) of the proposed new equation as dependent variable and the averaged value [(indirect calorimetry + estimated)/2] as independent variable [2].

Study objective (iii) GT3X VM cut points

PA intensity level is commonly defined according to MET [23] (moderate intensity: 3.00–5.99 METs; vigorous intensity: 6.00–8.99 METs; very vigorous intensity: ≥ 9 METs). The mathematical model used to build the equation to estimate MET from VM activity counts was an Artificial Neural Networks (ANN). An ANN is a mathematical model that emulates some of the observed properties of biological nervous system and draw on the analogies of adaptive biological learning. VM activity counts cut points were given according to the MET for PA intensity level classification [23]. 4 ANN were defined, one for each age-group and one for all participants. The first layer of each ANN (the input layer) corresponds to the independent variable (activity counts from VM), while the third layer (the output layer) corresponds to the dependent variable score (METs). The intermediate layer, which is a hidden layer (3 hidden units in each ANN) consists of all possible connections between the input and the output layer. The activation function for the hidden and output nodes was lineal, and function computed by the hidden unit was a logistic function. In order to obtain the synaptic weights of the ANN, the back-propagation algorithm was used [36], and the values for the algorithm parameters were 0.2 for the learning rate. The training of the network is stopped when the SSE falls below 0.00001 [35].

Sensitivity, specificity and area under the receiver operating characteristic curve (ROC-AUC value) [43] were also calculated to evaluate the ability of the new cut points to accurately classify the PA intensity level.

Statistical analyses were performed using PASW (Predictive Analytics SoftWare, v. 18.0 SPSS Inc., Chicago, IL, USA). Data is presented as mean ± standard deviation (SD), unless state otherwise. Significance level was set at $P \leq 0.05$. ANN-models were defined using the RSNNS software [4] and the study power of our design was calculated by the StatMate software, version 2.0 (GraphPad, San Diego, USA).

Results

Activity counts per axis increased with the intensity of activities (▶ **Fig. 1**) as well as EE values (METs) obtained with indirect calorimetry (▶ **Fig. 2**). Results are presented in METs to make comparisons across studies easier [42].

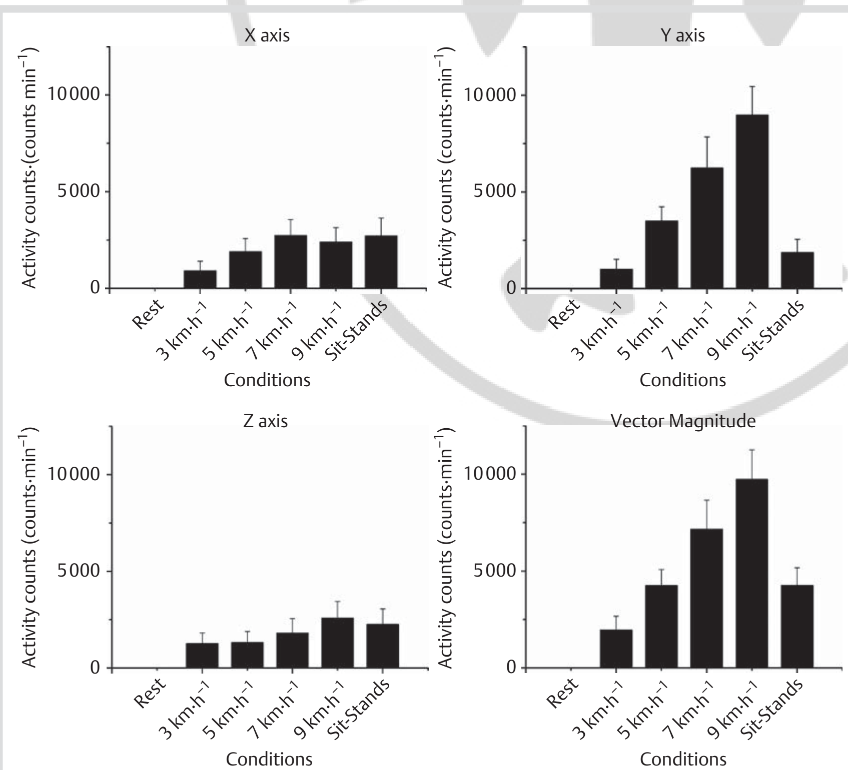

Fig. 1 Activity counts (counts·min^{-1}) (mean ± standard deviation) per axis and activities for all participants.

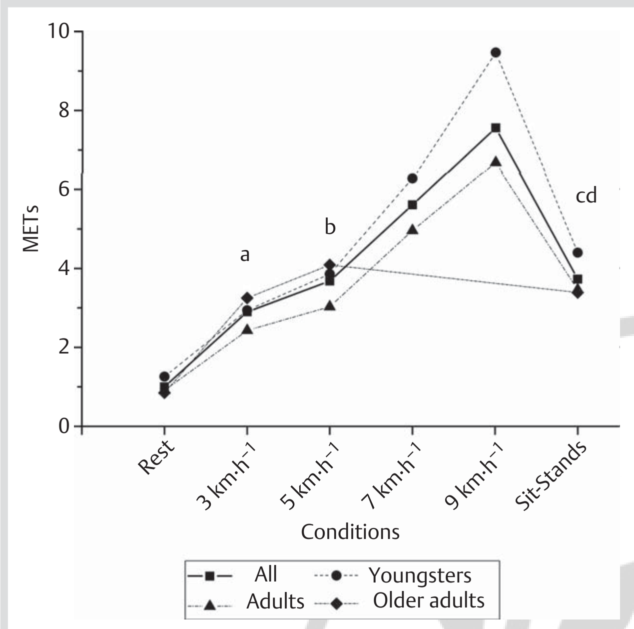

Fig. 2 Energy expenditure (in METs) determined by indirect calorimetry by activity for each age-group. [a] No significant different from sit-stand, older adults, P > 0.05. [b] No significant different from sit-stand, all participants, P > 0.05. [c] No significant different from 5 km·h^{-1}, all participants, P > 0.05. [d] No significant different from 3 km·h^{-1}, older adults, P > 0.05.

Comparison between EE estimated from the existing GT3X equations and EE measured with indirect calorimetry

EE values predicted from the equation provided by the Actigraph manual [15] and from the equation previously reported by Sasaki et al. [37] were compared with EE values obtained with indirect calorimetry. The results of BIAS (indirect calorimetry – EE predicted) and LOA are shown in **Table 1**. Following the criterion used by Crouter et al. [13], the less accurate equation was the work-energy theorem equation for adults using VM activity counts output (BIAS: −1.856; SD: 2.848; LOA: −7.437 to 3.725), whereas the most accurate equation was the Combined Equation in children using activity counts output from VM (BIAS: −0.053; SD: 1.776; LOA: −3.534 to 3.428).

Definition of new equations to estimate EE in youth, adults and older adults

The VM yielded a more accurate value of activity counts for EE prediction than the Y-axis. The best possible equations for VM and Y are shown in **Table 2**. The Bland and Altman plots for the VM are shown in **Fig. 3** and their BIAS (indirect calorimetry – EE predicted) are shown in **Table 1**.

The leave-one-out cross validation analysis confirmed the coefficients of each variable and the constant in each age group. The mean of the error and the SD of the error were −1.758 and 1.980 in all groups together, −1.571 and 1.864 in youth, −2.152 and 1.97 in adults, and 0.011 and 1.114 in older people respectively.

Table 1 BIAS, standard deviation of the BIAS (SD) and 95 % limits of agreement (LOA) for each age-group, in previously published and proposed equations.

Group	Axis	Author	Units	BIAS	SD	LOA	
All (n = 97; 49 women)	Y	Work-energy theorem	kcal · min^{-1}	0.4007	2.409	−4.321	5.122
		Combined	kcal · min^{-1}	0.5390	2.226	−3.824	4.902
	VM	Work-energy theorem	kcal · min^{-1}	0.8193	2.523	−5.764	4.125
		Combined	kcal · min^{-1}	−0.6365	2.342	−5.227	3.955
		Sasaki et al.	METs	−0.4115	1.695	−3.734	2.911
		New proposed	METs	−0.005955	1.396	−2.742	2.730
Youth (n = 31; 12 girls)	Y	Work-energy theorem	kcal · min^{-1}	0.5621	2.026	−3.409	4.533
		Combined	kcal · min^{-1}	0.8724	1.779	−2.614	4.358
	VM	Work-energy theorem	kcal · min^{-1}	−0.4481	2.008	−4.383	3.487
		Combined	kcal · min^{-1}	−0.05281	1.776	−3.534	3.428
		Sasaki et al.	METs	0.1967	3.340	−6.349	6.742
		Newly proposed	METs	−0.0012	1.486	−2.914	2.911
Adults (n = 31; 15 women)	Y	Work-energy theorem	kcal · min^{-1}	−0.6162	2.779	−6.063	4.831
		Combined	kcal · min^{-1}	−0.4281	2.437	−5.205	4.349
	VM	Work-energy theorem	kcal · min^{-1}	−1.856	2.848	−7.437	3.725
		Combined	kcal · min^{-1}	−1.547	2.435	−6.319	3.225
		Sasaki et al.	METs	−0.7283	3.641	−7.865	6.409
		Newly proposed	METs	−0.01050	1.199	−2.360	2.339
Older adults (n = 35; 22 women)	Y	Work-energy theorem	kcal · min^{-1}	1.530	1.679	−1.760	4.820
		Combined	kcal · min^{-1}	1.388	1.971	−2.476	5.251
	VM	Work-energy theorem	kcal · min^{-1}	0.07354	2.168	−4.175	4.323
		Combined	kcal · min^{-1}	−0.1753	2.485	−5.046	4.686
		Sasaki et al.	METs	−0.7590	2.836	−6.318	4.800
		Newly proposed	METs	0.004506	1.132	−2.215	2.224

Table 2 New equations proposed.

Group	Axis	Equation	R	R^2	SEE (±)	RMSE
All participants	Y	$METs = 3.14153 + 0.00057 \cdot Y\text{-axis } AC - 0.01380 \cdot BM - 0.00606 \cdot A$	0.78	0.60	1.45	1.45
(n = 97; 49 women)	VM	$METs = 2.7406 + 0.00056 \cdot VM\ AC - 0.008542 \cdot A - 0.01380 \cdot BM$	0.78	0.66	1.40	1.40
Youth	Y	$METs = 2.118079 + 0.000662 \cdot Y\text{-axis } AC$	0.81	0.65	1.56	1.55
(n = 31;12 girls)	VM	$METs = 1.546618 + 0.000658 \cdot VM\ AC$	0.83	0.68	1.49	1.49
Adults	Y	$METs\ (kcal \cdot min^{-1}) = 3.4002 + 0.00053 \cdot Y\text{-axis } AC - 0.05564 \cdot BM + 1.2789 \cdot G$	0.82	0.67	1.28	1.27
(n = 31;15 women)	VM	$METs = 2.8323 + 0.00054 \cdot VM\ AC - 0.05912 \cdot BM + 1.4410 \cdot G$	0.84	0.71	1.21	1.20
Older adults	Y	$METs\ (kcal \cdot min^{-1}) = 2.8867 + 0.00067 \cdot Y\text{-axis } AC - 0.6807 \cdot G$	0.50	0.36	1.18	1.17
(n = 35; 22 women)	VM	$METs = 2.5878 + 0.00047 \cdot VM\ AC - 0.6453 \cdot G$	0.64	0.41	1.14	1.13

Activity counts (AC): counts · min^{-1}; Age (A): years; Body mass (BM): Kg; Gender (G): women 1; man 2; R: correlation coefficient; R^2: coefficient of determination; SEE: standard error of the estimation; RMSE: root mean sum of squared errors

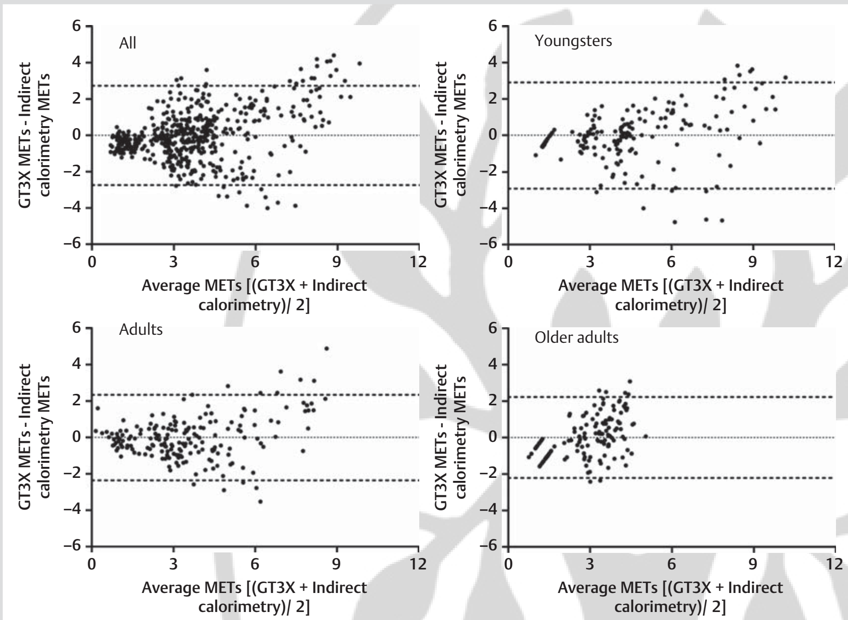

Fig. 3 Bland and Altman Plots in each group (energy expenditure (EE, in METs) determined with indirect calorimetry – EE (METs) predicted with GT3X).

For all age groups, the heteroscedasticity analysis showed a significant positive association (R = 0.528, P = 0.01) between the difference and the average of the EE measured with indirect calorimetry and the GT3X-estimated EE using the new proposed equation. We also found a significant positive association in youth (R = 0.558, P = 0.01) and adults (R = 0.536, P = 0.01), but not in older adults (R = 0.043, P = 0.615). Differences between EE predicted with the GT3X-new proposed equation and EE determined with indirect calorimetry are shown in **Fig. 4**.

GT3X VM cut points to classify PA intensity across age-groups

Activity cut points were determined from VM activity counts in each age-group using ANN model and are presented in **Table 3**. Values for youth were the lowest, whereas values were higher for adults than for older people in order to obtain the same METs intensity.

Values of the area under the ROC curve, sensitivity and specificity for the proposed cut points are shown in **Table 4**.

Discussion

The main study findings were as follows. First, the combined equation for MET estimation [15] (work-energy theorem, where counts per minute not exceed 1952 and Freedson equation, where counts exceed 1952 (kcal · min^{-1} = 0.00094 · *activity counts (counts · min^{-1})* + 0.1346 · *body mass (kg)* − 7.37418) yielded better results than the rest of previous available equations. Secondly, we defined a new, more accurate equation for each age-group: for all age-groups combined, *METs = 2.7406 + 0.00056 · VM activity counts (counts · min^{-1}) − 0.008542 · age (years) − 0.01380 · body mass (kg)*; for youth, *METs = 1.546618 + 0.000658 · VM activity counts (counts · min^{-1})*; for adults, *METs = 2.8323 + 0.00054 · VM activity counts (counts · min^{-1}) − 0.059123 · body mass (kg) + 1.4410 · gender (women = 1, men = 2)*; and for older people, *METs = 2.5878 + 0.00047 · VM activity counts (counts · min^{-1}) − 0.6453 · gender (women = 1, men = 2)*. Thirdly, we also defined new cut points in each group (**Table 3**). When evaluating the GT3X in the treadmill, we found that activity counts increased as walking/running speed increased, with the GT3X being able to differentiate among the different activities (**Fig. 1**). Sasaki et al. [37] obtained similar activity counts with the GT3X and

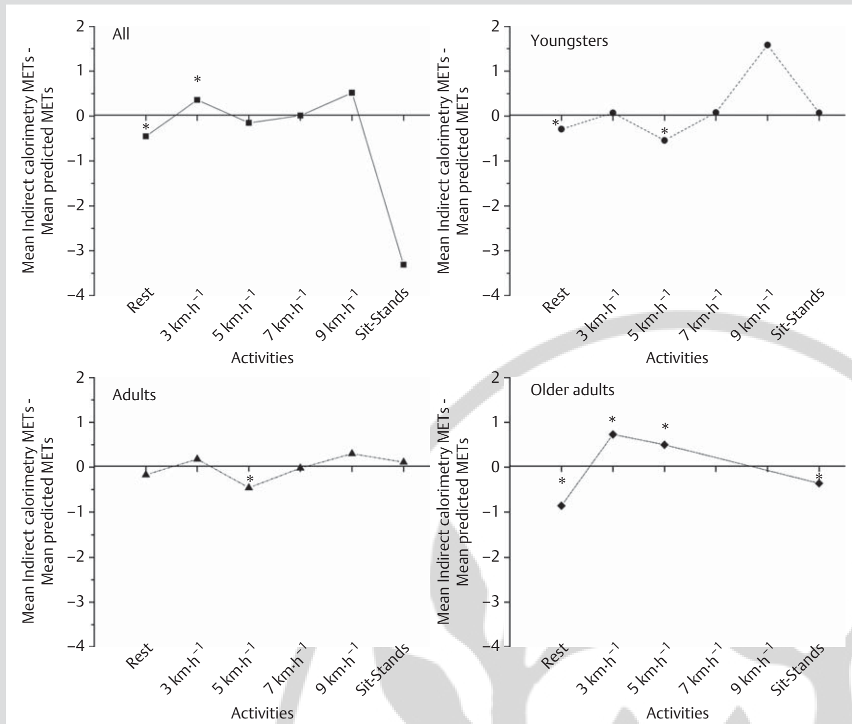

Fig. 4 Energy expenditure (EE, in METs) from indirect calorimetry vs. EE predicted with the GT3X for each age-group. *Significantly different from indirect calorimetry vs. predicted, same activity and age-group, $P<0.05$.

Table 3 Vector magnitude cut points for each age-group.

MET	All	Youth	Adults	Older adults
3	1480	2114	3208	2751
6	8505	6548	8565	9359
9	10500	11490	11593	–

Equation used to calculate cut points for:

All age-groups:

$\mathrm{METs}=((1/(1+\mathrm{EXP}(9.18694*((\mathrm{VM}-4027.474318)/3153.286042)+12.9723))*-3.05383+1/(1+\mathrm{EXP}(1.8487*(\mathrm{VM}-4027.474318)+2.55011))*-1.19096+1/(1+\mathrm{EXP}(3.84729*(\mathrm{VM}-4027.474318)+4.11932))*1.24936))*2.303724+3.733038$

BIAS = −0.2432; SD = 1.404; 95 % limit of agreement (LOA) = −2.995 to 2.509

Youth:

$\mathrm{METs}=((1/(1+\mathrm{EXP}(0.16215*((\mathrm{VM}-2507.143359)/1971.403158)+2.17929))*2.40308+1/(1+\mathrm{EXP}(0.16208*((\mathrm{VM}-2507.143359)/1971.403158)+2.18143))*2.40712+1/(1+\mathrm{EXP}(9.87464*((\mathrm{VM}-2507.143359)/1971.403158)+11.08109))*-2.49037)2.221964)+3.57993$

BIAS = −0.1740; SD = 1.433; LOA = −2.983 to 2.635

Adults:

$\mathrm{METs}=((1/(1+\mathrm{EXP}(-2.90002*(\mathrm{VM}-4648.8881)/3350.015592)+2.8147))*1.75949+1/(1+\mathrm{EXP}(1.20619*(\mathrm{VM}-4648.8881)/3350.015592)+2.53866))*-1.79643+1/(1+\mathrm{EXP}(2.61969*(\mathrm{VM}-4648.8881)/3350.015592)+4.57437))*-2.60096)*2.221964)+3.57993$

BIAS = 0.01220; SD = 1.307; LOA = −2.550 to 2.575

Older adults:

$\mathrm{METs}=((1/(1+\mathrm{EXP}(-4.6483*(\mathrm{VM}-4590.980124)/3311.158625)+2.70339))*1.11173+1/(1+\mathrm{EXP}(0.37229*(\mathrm{VM}-4590.980124)/3311.158625)+3.44165))*0.53061+1/(1+\mathrm{EXP}(2.3635*(\mathrm{VM}-4590.980124)/3311.158625)+2.52525))*-1.93496)*2.636543)+4.566316$

BIAS = −0.0716; SD = 0.8640; LOA = −1.765 to 1.622

Where METs is metabolic equivalents, and VM is vector magnitude

the GT1M, i.e. for the Y-axis, ~3 000 counts·min^{-1} at 4.8 km·h^{-1}, ~4 500 counts·min^{-1} at 6.4 km·h^{-1} and ~9 500 counts·min^{-1} at 9.7 km·h^{-1}; and for the VM, ~4 000 counts·min^{-1} at 4.8 km·h^{-1}, ~6 000 counts·min^{-1} at 6.4 km·h^{-1}, and ~10 000 counts·min^{-1} at 9.7 km·h^{-1}.

No studies are available addressing the accuracy of the Actilife equation for EE estimation with the GT3X, or potential differences in activity counts between the VM and the Y-axis with this accelerometer. Our results showed that the equations published in the Actilife manual do not appear sufficiently accurate for EE estimation. The most accurate values for EE prediction were obtained with the combined equation for activity counts in the Y-axis. In the older group, the best values corresponded to the work-energy theorem equation in the Y-axis. For the adult age-group, the best result corresponded to activity counts obtained with the combined equation in the Y-axis. However, among the young subjects, the best values for activity counts corresponded to the VM and the combined equation. We also tested the equation proposed by Sasaki et al. [37] using activity counts from the VM. However, the results were more accurate for all age-groups combined than for specific age-groups. Upon comparing our results with those of previous studies [19, 30–32, 41], it appeared necessary to develop a new equation for EE prediction, because the available equations are not sufficiently accurate.

In order to determine the best equation and axis to predict EE, we used the Bland-Altman approach [13] in each age-group. We found that the new equations we proposed are more accurate for EE estimation than the equation provided in the Actigraph manual or the one previously used by Sasaki et al. [37]. Further, in treadmill activities and in the sit-stand test, activity counts obtained from VM yielded a slightly more accurate prediction of EE than those obtained from the Y-axis. In contrast, Howe et al. [26] found that for the RT3 accelerometer the VM did not yield more accurate values of activity counts than the Y-axis. The results of the present study indicate that the GT3X provides an accurate estimation of EE during treadmill walking, except in older adults. Likewise, the new equations for adults and youth were more accurate for the entire group with the exception of the elderly. This could be due to the gaps in the age ranges of our sample. Fehling et al. [16] found that in older people the Caltrac accelerometer overestimated the EE of treadmill walking,

Table 4 Values of the area under the ROC curve, sensitivity (%) and specificity (%) for the proposed cut points per intensity and group.

		Light	Moderate	Vigorous	Very vigorous
All	Area	0.8	0.7	0.6	0.6
	Sensitivity (%)	89.9	56.6	24.4	21.4
	Specificity (%)	27.1	21.2	24.4	10.6
Youth	Area	0.8	0.7	0.7	0.6
	Sensitivity (%)	80.9	66.7	49.1	43
	Specificity (%)	18.1	22.3	19	18.6
Adults	Area	0.8	0.6	0.7	0.6
	Sensitivity (%)	84.6	52.2	46	43
	Specificity (%)	28.1	22.3	20	21
Older adults	Area	0.7	0.7		
	Sensitivity (%)	68.5	72.5		
	Specificity (%)	27.5	31.5		

(Area under the ROC curve; sensitivity (%); specificity(%))

whereas the Tritrac accelerometer underestimated the EE of this activity. Recent work by Strath et al. [44] also highlighted the lack of accurate equations for accelerometry-derived EE estimation in older adults.

Previous research has shown comparable activity count values in the Y-axis when using the GT1M or the GT3X accelerometer [37]. However, we demonstrated that for the GT3X accelerometer, the VM allowed for a more accurate EE prediction than the Y-axis. As such, it is necessary to identify VM cut points in different populations. With regards to this, Sasaki et al. [37] established the following VM cut points for young adults (26.9 ± 7.7 years): for moderate intensity activities (3–5.99 METs) 2690 to 6166 counts·min^{-1}; for hard activities (6–8.99 METs) 6167 to 9642 counts·min^{-1}; and for very hard activities (≥9 METS) >9642 counts·min^{-1}. The authors included the mean differences between actual and predicted METs (−0.3, −0.4, and 0.7 METs at 4.8, 6.4 and 9.7 km·h^{-1}, respectively), yet did not describe the values of the SD of BIAS. For the 3 age-groups we studied here, the mean differences were lower than those reported by Sasaki et al. [37], which could be explained by the fact that these authors assessed activity counts and METs only at three activities (4.8, 6.4 and 9.7 km·h^{-1}), whereas here we used six different activities or 'conditions' (including resting). In addition, Sasaki et al. established the cut-points value using linear regression. Another explanation could lie in the difference in the monitor firmware, as here we used the 4.1.0 firmware update, whereas Sasaki et al. used the firmware 1.3.0.

A main limitation of our design is that all tested activities (treadmill walking/running and sit-stands) were performed in a laboratory setting instead of being performed in free-living conditions. With regard to this situation, futures studies should assess the generalizability of laboratory-derived equations to free life settings, following recent recommendations by Staudenmater et al. [38]. Furthermore, other potential confounders, such as fitness level, adiposity and maturational status were not considered. Future research should cross-validate in different population cohorts the new equations we defined as well as improve the accuracy of the equations by controlling analyses for the aforementioned confounders. On the other hand, we believe our design has several strengths. We studied a relatively large sampling of subjects and 3 different age-groups. We also provided new equations to predict EE and new cut points for the use of VM activity counts in the different age-groups. Moreover, this is the first study comparing the accuracy of the VM vs. the Y-axis for EE prediction with the GT3X accelerometer.

To our knowledge this is the first study to (i) define cut points values by an ANN, or (ii) calculate ROC-AUC sensitivity and specificity for assessing the accuracy of the cut points being defined. The main limitation of the ANN is its complexity and its "black box" nature. The complexity of the ANN-equation may become rather inconvenient when applied in the field. Therefore, ANN was only used to define cut points and not for the new equations used to determine EE. The sensitivity and the specificity analysis revealed that the cut points were able to sufficiently distinguish the true positives, but not the true negatives. The latter finding was to be expected, because the monitor registers acceleration, and some PA patterns could be associated with large accelerations without an increment of the EE. However, in the event of an increment of EE, activity counts are always increased [28].

In conclusion, the GT3X appears to overall be an accurate tool for EE prediction, which proved sufficiently sensitive to discriminate between different intensities of PA, at least for activities performed in a laboratory setting. On the other hand, in order to use accurate GT3X VM cut points for EE estimation, these cut points have to be age-specific. Compared to more traditional uniaxial or biaxial devices, a technical step forward of the GT3X triaxial accelerometer for EE estimation during human PA performed in all axes is the higher accuracy of the VM vs. the Y-axis. However, more accurate equations for EE estimation are needed in older people.

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References

1 *Abel MG, Hannon JC, Sell K, Lillie T, Conlin G, Anderson D.* Validation of the Kenz Lifecorder EX and ActiGraph GT1M accelerometers for walking and running in adults. Appl Physiol Nutr Metab 2008; 33: 1155–1164
2 *Atkinson G, Davison RC, Nevill AM.* Performance characteristics of gas analysis systems: what we know and what we need to know. Int J Sports Med 2005; 26 (Suppl 1): S2–S10
3 *Bassett DR Jr, Ainsworth BE, Swartz AM, Strath SJ, O'Brien WL, King GA.* Validity of four motion sensors in measuring moderate intensity physical activity. Med Sci Sports Exerc 2000; 32: S471–S480

4 *Bergmeir C*, *Benítez J*. Neural Networks in R Using the Stuttgart Neural Network Simulator: RSNNS. J Stat Softw 2012; 46
5 *Bland JM*, *Altman DG*. Statistical methods for assessing agreement between two methods of clinical measurement. Lancet 1986; 1: 307–310
6 *Bouten CV*, *Westerterp KR*, *Verduin M*, *Janssen JD*. Assessment of energy expenditure for physical activity using a triaxial accelerometer. Med Sci Sports Exerc 1994; 26: 1516–1523
7 *Butte NF*, *Ekelund U*, *Westerterp KR*. Assessing physical activity using wearable monitors: measures of physical activity. Med Sci Sports Exerc 2012; 44: S5–S12
8 *CareFusion C*. Jaeger Oxycon Pro manual. Hoechberg, Germany: Care Fusion, 2009
9 *Chen KY*, *Bassett DR Jr*. The technology of accelerometry-based activity monitors: current and future. Med Sci Sports Exerc 2005; 37: S490–S500
10 *Chen KY*, *Sun M*. Improving energy expenditure estimation by using a triaxial accelerometer. J Appl Physiol 1997; 83: 2112–2122
11 *Colley RC*, *Tremblay MS*. Moderate and vigorous physical activity intensity cut-points for the Actical accelerometer. J Sports Sci 2011; 29: 783–789
12 *Crouter SE*, *Bassett DR Jr*. A new 2-regression model for the Actical accelerometer. Br J Sports Med 2008; 42: 217–224
13 *Crouter SE*, *Churilla JR*, *Bassett DR Jr*. Estimating energy expenditure using accelerometers. Eur J Appl Physiol 2006; 98: 601–612
14 *Crouter SE*, *Kuffel E*, *Haas JD*, *Frongillo EA*, *Bassett DR Jr*. Refined two-regression model for the ActiGraph accelerometer. Med Sci Sports Exerc 2010; 42: 1029–1037
15 *Engineering/Marketing A*. ActiLife users manual. Pensacola, FL: ActiGraph, 2009
16 *Fehling PC*, *Smith DL*, *Warner SE*, *Dalsky GP*. Comparison of accelerometers with oxygen consumption in older adults during exercise. Med Sci Sports Exerc 1999; 31: 171–175
17 *Freedson P*, *Bowles HR*, *Troiano R*, *Haskell W*. Assessment of physical activity using wearable monitors: recommendations for monitor calibration and use in the field. Med Sci Sports Exerc 2012; 44: S1–S4
18 *Freedson P*, *Pober D*, *Janz KF*. Calibration of accelerometer output for children. Med Sci Sports Exerc 2005; 37: S523–S530
19 *Freedson PS*, *Melanson E*, *Sirard J*. Calibration of the Computer Science and Applications, Inc. accelerometer. Med Sci Sports Exerc 1998; 30: 777–781
20 *Hall KS*, *Howe CA*, *Rana SR*, *Martin CL*, *Morey MC*. METs and Accelerometry of Walking in Older Adults: Standard vs. Measured Energy Cost. Med Sci Sports Exerc 2012 in press
21 *Hanggi JM*, *Phillips LR*, *Rowlands AV*. Validation of the GT3X ActiGraph in children and comparison with the GT1M ActiGraph. J Sci Med Sport 2013; 16: 40–44
22 *Harriss DJ*, *Atkinson G*. Update – ethical standards in sport and exercise science research. Int J Sports Med 2013; 16: 819–821
23 *Haskell WL*, *Lee IM*, *Pate RR*, *Powell KE*, *Blair SN*, *Franklin BA*, *Macera CA*, *Heath GW*, *Thompson PD*, *Bauman A*. Physical activity and public health: updated recommendation for adults from the American College of Sports Medicine and the American Heart Association. Med Sci Sports Exerc 2007; 39: 1423–1434
24 *Hendelman D*, *Miller K*, *Baggett C*, *Debold E*, *Freedson P*. Validity of accelerometry for the assessment of moderate intensity physical activity in the field. Med Sci Sports Exerc 2000; 32: S442–S449
25 *Hooker SP*, *Feeney A*, *Hutto B*, *Pfeiffer KA*, *McIver K*, *Heil DP*, *Vena JE*, *Lamonte MJ*, *Blair SN*. Validation of the actical activity monitor in middle-aged and older adults. J Phys Act Health 2011; 8: 372–381
26 *Howe CA*, *Staudenmayer JW*, *Freedson PS*. Accelerometer prediction of energy expenditure: vector magnitude versus vertical axis. Med Sci Sports Exerc 2009; 41: 2199–2206
27 *Hussey J*, *Bennett K*, *Dwyer JO*, *Langford S*, *Bell C*, *Gormley J*. Validation of the RT3 in the measurement of physical activity in children. J Sci Med Sport 2009; 12: 130–133
28 *Kozey SL*, *Lyden K*, *Howe CA*, *Staudenmayer JW*, *Freedson PS*. Accelerometer output and MET values of common physical activities. Med Sci Sports Exerc 2010; 42: 1776–1784
29 *Lamarra N*, *Whipp BJ*, *Ward SA*, *Wasserman K*. Effect of interbreath fluctuations on characterizing exercise gas exchange kinetics. J Appl Physiol 1987; 62: 2003–2012
30 *Maddison R*, *Jiang Y*, *Hoorn SV*, *Mhurchu CN*, *Lawes CM*, *Rodgers A*, *Rush E*. Estimating energy expenditure with the RT3 triaxial accelerometer. Res Q Exerc Sport 2009; 80: 249–256
31 *Matthew CE*. Calibration of accelerometer output for adults. Med Sci Sports Exerc 2005; 37: S512–S522
32 *Mattocks C*, *Leary S*, *Ness A*, *Deere K*, *Saunders J*, *Tilling K*, *Kirkby J*, *Blair SN*, *Riddoch C*. Calibration of an accelerometer during free-living activities in children. Int J Pediatr Obes 2007; 2: 218–226
33 *Puyau MR*, *Adolph AL*, *Vohra FA*, *Butte NF*. Validation and calibration of physical activity monitors in children. Obes Res 2002; 10: 150–157
34 *Rothney MP*, *Brychta RJ*, *Meade NN*, *Chen KY*, *Buchowski MS*. Validation of the ActiGraph two-regression model for predicting energy expenditure. Med Sci Sports Exerc 2010; 42: 1785–1792
35 *Ruiz JR*, *Ramirez-Lechuga J*, *Ortega FB*, *Castro-Pinero J*, *Benitez JM*, *Arauzo-Azofra A*, *Sanchez C*, *Sjostrom M*, *Castillo MJ*, *Gutierrez A*, *Zabala M*, *Group HS*. Artificial neural network-based equation for estimating VO2max from the 20 m shuttle run test in adolescents. Artif Intell Med 2008; 44: 233–245
36 *Rumelhart D*, *Hinton G*, *Williams R*. Learning representations of back-propagation errors. Nature 1985; 323: 3
37 *Sasaki JE*, *John D*, *Freedson PS*. Validation and comparison of ActiGraph activity monitors. J Sci Med Sport 2011; 14: 411–416
38 *Staudenmayer J*, *Zhu W*, *Catellier DJ*. Statistical considerations in the analysis of accelerometry-based activity monitor data. Med Sci Sports Exerc 2012; 44: S61–S67
39 *Strath SJ*, *Bassett DR Jr*, *Swartz AM*. Comparison of MTI accelerometer cut-points for predicting time spent in physical activity. Int J Sports Med 2003; 24: 298–303
40 *Trost SG*, *Loprinzi PD*, *Moore R*, *Pfeiffer KA*. Comparison of accelerometer cut points for predicting activity intensity in youth. Med Sci Sports Exerc 2011; 43: 1360–1368
41 *Welk GJ*, *Eisenmann JC*, *Schaben J*, *Trost SG*, *Dale D*. Calibration of the biotrainer pro activity monitor in children. Pediatr Exerc Sci 2007; 19: 145–158
42 *Welk GJ*, *McClain J*, *Ainsworth BE*. Protocols for evaluating equivalency of accelerometry-based activity monitors. Med Sci Sports Exerc 2012; 44: S39–S49
43 *Zweig MH*, *Campbell G*. Receiver-operating characteristic (ROC) plots: a fundamental evaluation tool in clinical medicine. Clin Chem 1993; 39: 561–577
44 *Strath SJ, Pfeiffer KA, Whitt-Glover MC*. Accelerometer use with children, older adults, and adults with functional limitations. Med Sci Sports Exerc 2012; 44: S77–S85