Manuscript Details

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Title	Accelerometry calibration in people with class II-III obesity: Energy expenditure prediction and physical activity intensity identification
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Abstract

Background: Almost all accelerometer calibration studies were developed for non-obese people, which hampers an accurate prediction of energy expenditure (EE) and induces a misclassification of sedentary activity (SA) and physical activity intensities (PAI) in class II-III obese people. Research Question: The purpose of this study was to develop regression equations to predict EE and cut-points to classify SA and PAI in severe obese people based on several metrics obtained from hip and back accelerometer placement data. Methods: 43 class II-III obese participants performed a protocol that included sitting and standing positions and walking at several speeds. During the protocol participants wore an accelerometer at hip and back, and respiratory gas exchange was measured by indirect calorimetry. Accelerometer metrics analyzed were: activity counts, mean amplitude deviation and euclidean norm minus one. EE was predicted through linear mixed models while cut-points to classify SA and PAI were obtained applying receiver operating characteristic curves. Leave-one-out cross-validation data was used to calculate Bland-Altman plots, prediction accuracy, Kappa statistic and percent agreement. Results: All prediction models presented a quadratic equation that had as predictors age and one of the accelerometer metrics. Predicted EE indicated a good agreement and a root mean square error below 1.02 kcal·min−1. Global classification agreement from developed cut-points was categorized as almost perfect with a percent agreement above 84%. Prediction accuracy and classification agreement were similar among accelerometer metrics in each position and between them in hip and back placement. Significance: Hip and back accelerometer data collected in severe obese people allow to accurately estimate EE and to correctly classify SA and PAI. These results enable future studies to adopt appropriate regression equations and cut-points developed for class II-III obese people rather than those established for non-obese people.

Keywords	indirect calorimetry; raw acceleration; severe obesity; validity; activity monitor;
Taxonomy	Measurement Technique, Accelerometer

Corresponding Author	Florencio Sousa
Order of Authors	Florencio Sousa, Lucas Veras, Jose Ribeiro, GIORJINES BOPPRE, Vítor Devezas, Hugo Santos-Sousa, John Preto, Leandro Machado, J. Paulo Vilas-Boas, José Oliveira, Hélder Fonseca
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Cover Letter

Florêncio Sousa
Faculty of Sport, University of Porto
Rua Dr. Placido Costa, 91
4200-450 Porto, Portugal

April 7, 2019

Dear Editor,

We hereby submit the manuscript entitled "Accelerometry calibration in people with class II-III obesity: Energy expenditure prediction and physical activity intensity identification". We would like to have the manuscript considered for publication in Gait & Posture. We developed regression equations to predict energy expenditure and cut-points to classify physical activity intensities in severe obese people based on several metrics obtained from hip and back accelerometer placement data.

This original research article responds to a gap that exists in physical activity assessment methodology in a specific population. Because class II-III obesity prevalence has increased alarmingly in the last years, this article is useful for researchers from both exercise and health fields that are devoted to understand the relation between physical activity levels in patients with severe obesity and their association with health outcomes. Our results enable future studies to adopt appropriate regression equations and cut-points for class II-III obese people rather than those established for non-obese people. Hence, we believe our findings would be of great interest to the Gait & Posture readers.

This article presents several strengths: i) it is the first calibration study developed for patients with severe obesity using triaxial accelerometers; ii) calibration results were developed based on raw acceleration metrics, which allow comparisons between different studies regardless of the accelerometer brand used and offers more transparency because the computation process that can be executed in open-source packages; and iii) complete description of data processing and statistical analyzes conducted using R statistical software is available in an open platform, associated with a digital object identifier.

This manuscript has not been published and is not under consideration for publication elsewhere. All authors substantially contributed to this manuscript. None of the authors have any conflicts of interest to disclose.

Please address all correspondence concerning this manuscript to me at joseflorenciosousa@gmail.com.

Thank you for your consideration of this manuscript.

Sincerely,

Florêncio Sousa
On behalf of the co-authors

- Severe obese people´s EE can be accurately predicted by accelerometry data
- SA and PAI in severe obese people can be identified with accelerometer cut-points
- Data from hip and back placements and AC, MAD and ENMO metrics are valid options

Accelerometry calibration in people with class II-III obesity: Energy expenditure prediction and physical activity intensity identification

Florêncio Diniz-Sousa[a], Lucas Veras[a], José Carlos Ribeiro[a], Giorjines Boppre[a], Vítor Devezas[b], Hugo Santos-Sousa[b], John Preto[b], Leandro Machado[c,d], João Paulo Vilas-Boas[c,d], José Oliveira[a], Hélder Fonseca[a,b]

[a] Research Center in Physical Activity, Health and Leisure (CIAFEL), Faculty of Sport, University of Porto, Porto, Portugal

[b] General Surgery Department, São João Medical Center, Porto, Portugal

[c] Center of Research, Education, Innovation and Intervention in Sport (CIFI2D), Faculty of Sport, University of Porto, Porto, Portugal

[d] Biomechanics Laboratory (LABIOMEP-UP), University of Porto, Porto, Portugal

Corresponding author name: Florêncio Diniz-Sousa

Mailing address:

Faculty of Sport, University of Porto

Rua Dr. Placido Costa, 91

4200-450 Porto, Portugal

Telephone: +351 220425202

Fax: +351 2255006867

E-mail: joseflorenciosousa@gmail.com

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Abstract

Background: Almost all accelerometer calibration studies were developed for non-obese people, which hampers an accurate prediction of energy expenditure (EE) and induces a misclassification of sedentary activity (SA) and physical activity intensities (PAI) in class II-III obese people.

Research Question: The purpose of this study was to develop regression equations to predict EE and cut-points to classify SA and PAI in severe obese people based on several metrics obtained from hip and back accelerometer placement data.

Methods: 43 class II-III obese participants performed a protocol that included sitting and standing positions and walking at several speeds. During the protocol participants wore an accelerometer at hip and back, and respiratory gas exchange was measured by indirect calorimetry. Accelerometer metrics analyzed were: activity counts, mean amplitude deviation and euclidean norm minus one. EE was predicted through linear mixed models while cut-points to classify SA and PAI were obtained applying receiver operating characteristic curves. Leave-one-out cross-validation data was used to calculate Bland-Altman plots, prediction accuracy, Kappa statistic and percent agreement.

Results: All prediction models presented a quadratic equation that had as predictors age and one of the accelerometer metrics. Predicted EE indicated a good agreement and a root mean square error below 1.02 kcal·min^{-1}. Global classification agreement from developed cut-points was categorized as almost perfect with a percent agreement above 84%. Prediction accuracy and classification agreement were similar among accelerometer metrics in each position and between them in hip and back placement.

Significance: Hip and back accelerometer data collected in severe obese people allow to accurately estimate EE and to correctly classify SA and PAI. These results enable future studies to adopt appropriate regression equations and cut-points developed for class II-III obese people rather than those established for non-obese people.

1 Introduction

Physical activity assessment by accelerometry is increasingly widespread in research field. Although it is an objective method, data obtained by accelerometers should be translated into more interpretable information. This can be achieved by a calibration process to determine a standard measurement[1]. In most of the calibration studies, linear acceleration recorded by accelerometer is converted into manufacturer-specific units, usually mentioned as "activity counts" (AC). Unfortunately, this is an arbitrary unit defined by manufacturers software applying their own approach (i.e., filters, amplifiers, algorithms). For this reason, the meaning of AC is not the same among brands, which hinders the use of calibration results among studies that utilize different devices. This situation has been inducing misconceptions and hampers successful methodological decisions.

In the last years, several new metrics have been proposed to solve these limitations[2]. These approaches provide standard metrics and have in common their construction based on acceleration (usually in g-units). Two of these metrics are mean amplitude deviation (MAD)[3] and euclidean norm minus one (ENMO)[4]. Their properties are known, and they are nonproprietary metrics. Further, they can be computed using open-source packages, thus, meeting the recommendation for more transparency[5]. Although low agreement seems to occur in sedentary tasks, some findings have shown that, when applying similar methodology, these universal metrics allow comparisons between results regardless of accelerometer brands[6].

Until now, calibration studies that applied these metrics have been done for children[7], adolescents[8], adults[6, 7] and elderly[9]. These studies are required because the results are only valid for a population with similar characteristics to those of the utilized sample, such as age, body composition, physical fitness or health condition[10]. Obese people, especially those with severe obesity, are characterized by low resting metabolic rate (RMR)[11], higher energetic walking cost[12] and lower aerobic physical fitness[13]. These factors may promote different regression equations to predict energy expenditure (EE) and different cut-points to classify sedentary activity (SA) and physical activity intensities (PAI), when compared with calibration studies that use a normal body mass index (BMI) sample. Moreover, severe obese people present often a high fat panniculus amount, that may introduce some noise in the accelerometer data, which, theoretically, might induce lower accuracy results in hip rather than in back placement[14].

To our best knowledge, there is no calibration study based on raw accelerations developed for severe obese people. Hence, a reference calibration for this population is necessary, wherein not only the new metrics must prove to be valid, but also show an equal or superior accuracy compared with established AC units[1]. Therefore, the main purpose of this study was to develop regression equations to predict EE and cut-points to classify SA and PAI in severe obese people based on several metrics obtained from hip and back accelerometer placement data.

2 Methods

2.1 Participants

Forty-three class II-III Caucasian adult obese individuals (11 males, 32 females; age: 42.6±9.2 yrs; height: 161.2±9.0 cm; body mass: 112.6±16.7 kg; BMI: 43.2±4.5 kg·m^{-2}; percent whole-body fat: 48.5±5.1%; $\bar{X}$±SD) were recruited for this study. Before giving their written informed consent, participants were informed about the purpose and protocol of the research. The study was approved by the local Ethics Committee.

Height, body mass and body composition were assessed following the standard procedures by a mounted stadiometer, a digital scale and a dual-energy X-ray absorptiometry, respectively. Before attending the protocol, participants were maintained awake in a lying rest position for 20 min to improve measurement conditions of RMR.

2.2 Protocol

The protocol was divided into three parts. First, the participant rested in a sitting position for 10 minutes. Second, the participant remained quiet in standing position for 3 minutes. Third, participant initialized an incremental sub-maximal test on the treadmill, with no inclination, at 2 or 3 km·h^{-1} (0.56 or 0.83, m·s^{-1}), depending on the participant's perceived comfortable walking speed. The treadmill speed increased 1 km·h^{-1} (0.28 m·s^{-1}) at each 4 min, with no rest time among speeds. The walking phase ended at 6 km·h^{-1} (1.67 m·s^{-1}) or before if 60% of heart rate reserve was achieved or at the participant's request. Participants were not allowed to hold handrails during the walking phase.

2.3 Measurements

During the protocol, respiratory gas exchange was measured by indirect calorimetry using a metabolic cart (Oxycon Pro Metabolic Cart, CareFusion, Höchberg, Germany). Oxygen uptake (VO_2) and carbon dioxide production (CO_2) were measured breath-by-breath and averaged over 5 s epochs. Heart rate was also recorded by a heart rate monitor chest strap. The values of VO_2 and VCO_2 were used to calculate EE with the Weir's equation[15].

Participants also wore two activity monitors, secured on the same elastic belt with a belt clip, during the standing and walking phase protocol, one at their right hip and another at their lower back.

The activity monitors used were a GT9X Link (ActiGraph, Pensacola, FL, USA) that incorporates a primary and a secondary triaxial accelerometers. Manufacturer software defines that AC are only obtained from primary accelerometer data and these are computed according to proprietary procedures. The secondary accelerometer was used to obtain raw acceleration data because, unlike the primary accelerometer, manufacturer software does not apply any filtering on its data. Both primary and secondary accelerometers were programmed to collect data at a 100 Hz sampling frequency. AC were computed based on resultant vector data into 5 s epochs by manufacturer software.

2.4 Data processing and statistical analyses

Data processing and statistical analyses were conducted using R statistical software (R version 3.5.0, R Foundation for Statistical Computing, Vienna, Austria). Subsequent data analyses for all parameters were conducted with the penultimate 30 s of sitting position, standing position and all walking speeds, ensuring respiratory gas exchange steady state. The last 30 sec of each protocol period were not included in the data analyses to avoid the incorporation of transitional movements. MAD[3] and ENMO[4] metrics were computed with GGIR package (version 1.6-7). All these metrics were computed based on resultant vector raw acceleration, stored using 5 s epochs and expressed in milligravity units (mg). Then, the average from 5 s epochs of each protocol period was posteriorly used in statistical analysis.

Statistical analyses were registered in an open platform[16], where R code utilized in each analysis was described and more detailed result information was presented.

Linear mixed models (LMM) were applied to predict EE. Distinct LMMs were developed with data from hip and back accelerometer placement. AC, MAD, ENMO, sex, age, body mass and BMI were tested as fixed effects, but only body mass and the accelerometer metrics have shown to be significant predictors. Although random slopes have been tested, only the inclusion of random intercept has showed model improvement. Linear, quadratic and cubic polynomial simulations were also tested, whereas the last one did not contribute significantly to the models. Coefficient of determination (R^2) was also calculated.

Cut-points that identify SA and PAI created from AC, MAD and ENMO were obtained applying receiver operating characteristic curves (ROC), for both hip and back accelerometer placement data. The indices used to summarize the cut-points were sensitivity, specificity and the area under the curve. RMR represented by VO_2 ($ml \cdot kg^{-1} \cdot min^{-1}$) data from sitting position period was used to calculate the metabolic equivalent (MET) for each participant and were not used in the ROC analyses. Activities were classified as: ≤ 1.5 MET – SA; 1.6–2.9 MET – light physical activity (LPA); 3.0–6.0 MET – moderate physical activity (MPA); and >5.5 MET – vigorous physical activity (VPA)[17]. LPA boundaries were provided with SA and MPA cut-points.

The validity of equations and cut-points developed were posteriorly analyzed through leave-one-out cross-validation (LOOCV) method. Dataset obtained from LOOCV were used in the following validation analyses.

Agreement between EE obtained from indirect calorimetry and predicted EE was assessed by Bland-Altman plots. Bias and the limits of agreement with 95% confidence intervals (LoA) were calculated. Linear regression was applied to identify if there was any proportional bias.

The accuracy of predicted EE was assessed by mean absolute error (MAE), mean absolute percent error (MAPE), and root mean square error (RMSE). Although there is no standard index nor threshold that defines what is an acceptable error for the EE prediction, based on previous findings in this field [18], we considered an accurate prediction those results that had a < 1.30 $kcal \cdot min^{-1}$ RMSE.

Kappa statistic (κ) was used to measure the classification agreement of SA and PAI obtained from indirect calorimetry and those obtained from cut-points. Individual classification agreement analyses for SA, LPA, MPA and VPA were done with unweighted Kappa method and global classification agreement utilizing a quadratic weighted Kappa method. A Kappa coefficient of <0 is considered poor, .00–.20 slight, .21–.40 fair, .41–.60 moderate, .61–.80 substantial, and .81–1.00 almost perfect[19]. Percent agreement from global classification was also calculated.

Accuracy comparison of predicted EE among accelerometer metrics in each hip and back placement was analyzed using the absolute errors through the analysis of variance (ANOVA). Absolute errors were also used to compare prediction accuracy between hip and back placement for each accelerometer metric by the independent two-sample t-test. Absolute values of classification error were utilized to compare classification agreement among accelerometer metrics in each position through Kruskal-Wallis test and to compare each accelerometer metric between hip and back placement through Wilcoxon rank-sum test.

The statistically significant value was set as $\alpha = 0.05$.

3 Results

Table 1 shows regression equations developed for all accelerometer metrics from hip and back placement, their R^2 and accuracy indices. In all analyses R^2 was higher than 0.85, MAE ranged from 0.67 to 0.79 kcal·min^{-1}, MAPE from approximately 14% to 18% and RMSE from 0.88 to 1.02 kcal·min^{-1}.

Bland-Altman plots in Figure 1 have presented in all analyses a good agreement between measured and predicted EE, with an irrelevant bias ($p > 0.05$) and few data points outside LoA. Non-proportional bias was detected ($p > 0.05$).

Table 2 presents the cut-points developed for all accelerometer metrics from hip and back placement with their sensitivity, specificity and area under the curve. Individual and global classification agreement analyses as well as percent agreement from global classification are also presented on Table 2. Individual classification agreement analyses have shown that all SA classification was categorized as almost perfect, MPA as moderate or substantial and VPA as moderate. All global classification agreements were categorized as almost perfect with a percent agreement above 83%.

Comparison among accelerometer metrics in each position and between them in hip and back placement has shown no significant differences in accuracy of predicted EE and in classification agreement ($p > 0.05$).

4 Discussion

The aim of this study was to develop regression equations to predict EE and cut-points to classify SA and PAI in individuals with severe obesity based on several metrics obtained from hip and back accelerometer placement data. Our results showed that all regression equations and cut-points developed for both hip and back placements are valid regardless of the accelerometer metric used.

Our results have shown that the new metrics based on raw acceleration allow to achieve similar calibration results compared with established AC units. This was observed in estimated EE, with an almost equal prediction error and in cut-points, with comparable classification agreement. These results seem to enable to argue that raw acceleration metrics should be adopted rather than AC, since, beyond valid, they allow greater calibration results applicability on different accelerometer types. However, currently there is no consensus about the metric that should be adopted as reference(2). For this reason, we decided to utilize two raw acceleration metrics that have gained prominence in the literature, so that future studies that assess physical activity in severe obese people could compare with the metric that they consider most appropriate.

Calibration results between hip and back placement were also analyzed. Some researchers have already shown that collected data can be slightly different depending on accelerometer placement on waist circumference(20) or BMI level(14). However, this does not seem to affect the study results, such as predicted EE, if an adequate regression equation is applied to a specific placement(21). Our results seem to corroborate with those findings, since both hip and back accelerometer placement present similar accuracy of predicted EE and equal classification agreement. Since back accelerometer placement has some utilization limitations (e.g. uncomfortable device back pressure in sitting position), we advocate that hip placement should continue to be used as conventional position on waist circumference.

Results found with regression equations showed good accuracy and are in line with previous calibration studies(20, 22). Freedson *et al*.(22), who evaluated a non-obese sample in a treadmill protocol, also have shown that most of EE variance can be explained by AC and weight data, with standard error of the estimate of 1.40 kcal·min^{-1}. Our prediction models were conducted through LMM, because independence assumption among observations was violated with repeated measures (participants walking at several speeds) and traditional multiple linear regressions are not recommended in these situations[23]. Other advantage from LMM utilization was the inclusion of random intercept that improved prediction models. This statistical option also allowed to verify a significant quadratic relationship between EE and accelerometer metrics. These results support the findings obtained by Aadland *et al*.[24] who found the same relationship in obese subjects that walked on a treadmill at several speeds.

The cut-points proposed here to classify PAI are substantially below from those proposed in the literature[25]. There is only one study that has analyzed obese-to-severe obese people that has applied a similar methodology to ours, whose results cannot be compared, as they used a uniaxial accelerometer to obtain AC, thus, the metrics do not mean the same[24]. Comparing the cut-points of those studies that obtained AC from resultant vector data in non-obese people, we found that our MPA were more than 30% lower[26, 27]. Cut-points for severe obese people are also mostly below when metrics were based on raw acceleration[7, 20], although with a smaller difference. Class II-III obesity has increased alarmingly in the last years. An accurate measurement is essential to understand the true physical activity levels of these people and apply the correct strategies to diminish this disease. Hence, this study can be a step forward, inasmuch as future researches can adopt appropriate cut-points for severe obese people instead of those developed for non-obese people.

Nowadays, due to its impact on health outcomes, one of the main research focuses in physical activity is to quantify the amount of time spent in tasks with low EE (≤1.5 METs), generally called as sedentary. To capture this category with cut-points, we decided to include a quiet standing position, which promoted an EE around 1.0 to 1.5 METs in almost all participants. Therefore, what was measured was SA[17] and not sedentary behavior which does not include standing position tasks[28]. Although the inclusion of sedentary behavior tasks in our protocol was not possible due to logistic restrictions, some studies have shown that distinction between sedentary behavior and quiet standing position is difficult utilizing data obtained from accelerometry[6, 9]. Hence, the cut-point proposed to classify SA from the several metrics, theoretically, could be also used to classify sedentary behavior. However, more studies are needed to confirm this hypothesis.

This study has some limitations. First, although a substantial part of the day is spent in a standing position and in ambulatory tasks performed at low walking speeds[29], our protocol did not include sufficient activities that have fully represented severe obese people lifestyle[1, 10]. Second, a different sample for model validation was not available, thus a dataset created from LOOCV method was used as recommended for this situation[23].

5 Conclusions

Hip and back accelerometer data collected in severe obese people allowed to accurately estimate EE and correctly classify SA and PAI. These findings enable future studies to adopt appropriate regression equation and cut-points developed for class II-III obese people rather than those established for non-obese people.

Declarations of interest: none.

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Figure Legend

Figure 1. Bland-Altman plots of measured and predicted EE in all accelerometer metrics from hip (left panel, A) and back (right panel, B) placement. Continuous thick lines show bias while dotted lines show upper and lower limits of agreement.

Abbreviations: AC, activity counts; ENMO, euclidean norm minus one; MAD, mean amplitude deviation.

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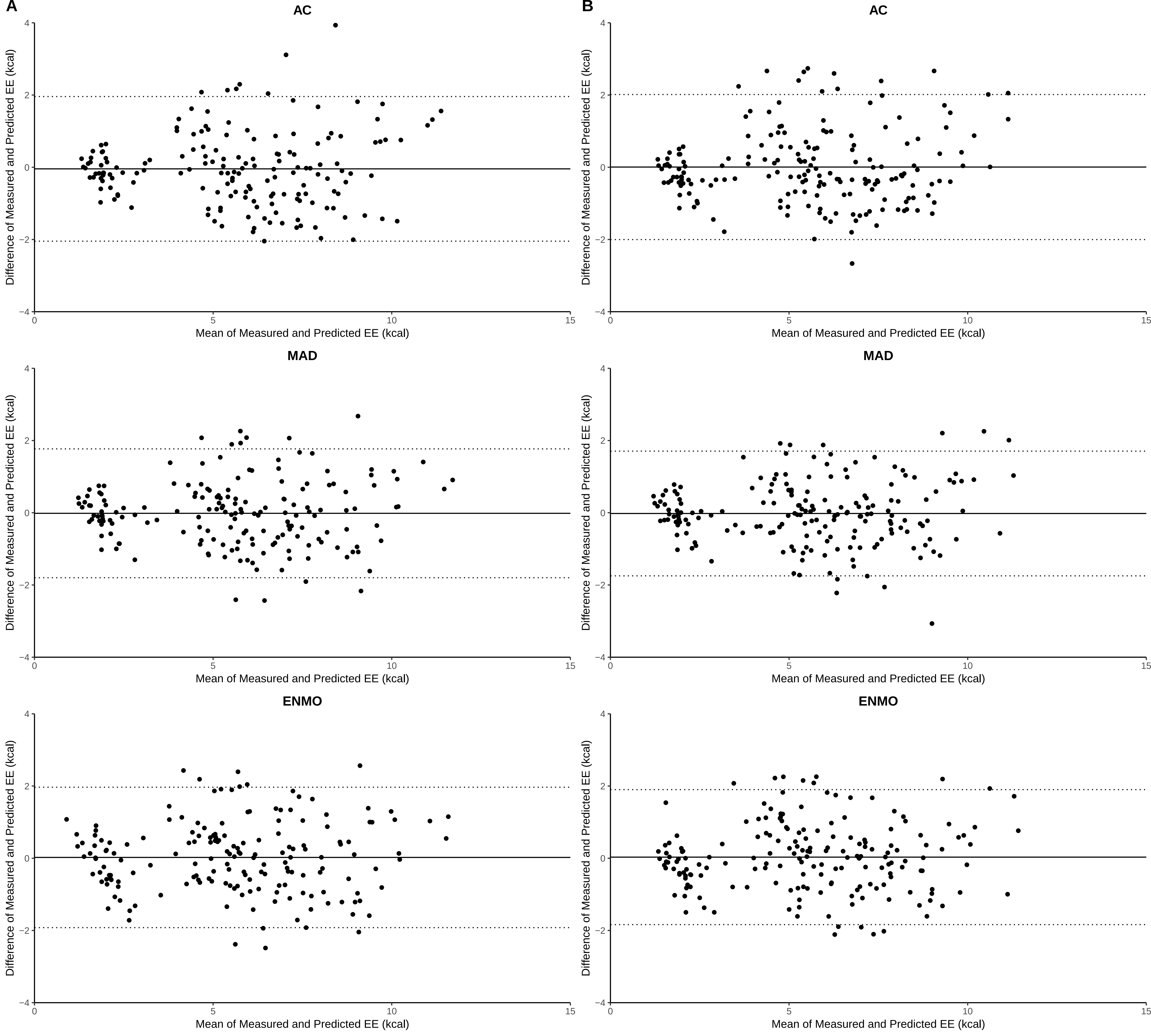
A
B
AC
MAD
ENMO
Difference of Measured and Predicted EE (kcal)
Mean of Measured and Predicted EE (kcal)
4
2
0
−2
−4
0
5
10
15

Table 2. Regression equations, R^2 and accuracy indices.

Accelerometer Placement	Metric	Regression equations	R^2	MAE	MAPE	RMSE
Hip	AC	EE ($kcal \cdot min^{-1}$) = - 1.5333483 + 0.0167347(AC) - 0.0000050(AC^2) + 0.0318617(body mass)	0.88	0.78	14.96%	1.02
	MAD	EE ($kcal \cdot min^{-1}$) = - 2.3840820 + 0.0227323(MAD) - 0.0000126(MAD^2) + 0.0385458(body mass)	0.90	0.70	14.28%	0.91
	ENMO	EE ($kcal \cdot min^{-1}$) = - 3.227561 + 0.043079(ENMO) - 0.000047($ENMO^2$) + 0.039445(body mass)	0.88	0.79	17.66%	0.99
Back	AC	EE ($kcal \cdot min^{-1}$) = - 1.9328019 + 0.0220189(AC) - 0.0000147(AC^2) + 0.0365243(body mass)	0.86	0.78	16.04%	1.02
	MAD	EE ($kcal \cdot min^{-1}$) = - 2.5430811 + 0.0295663(MAD) - 0.0000264(MAD^2) + 0.0398809(body mass)	0.90	0.67	13.83%	0.88
	ENMO	EE ($kcal \cdot min^{-1}$) = - 4.135593 + 0.060027(ENMO) - 0.000093($ENMO^2$) + 0.041895(body mass)	0.88	0.74	16.18%	0.95

Abbreviations: AC, activity counts; ENMO, euclidean norm minus one; kcal, kilocalorie; MAD, mean amplitude deviation; MAE, mean absolute error; MAPE, mean absolute percent error; R^2, coeffient of determination; RMSE, root mean square error.

Table 3. Proposed cut-points and their classification agreement.

		Cutpoint (5-s epochs)	ROC			Kappa		Percent agreement
			Sensitivity	Specificity	AUC (95% CI)	Individual agreement	Global agreement	
Hip	**AC**							
	Sedentary	68	1.00	0.98	0.99 (0.97-1.00)	0.95		
	Moderate	130	0.98	0.81	0.83 (0.73-0.93)	0.81	0.94	90%
	Vigorous	463	0.89	0.96	0.96 (0.92-1.00)	0.55		
	MAD							
	Sedentary	45	1.00	0.98	0.98 (0.96-1.00)	0.95		
	Moderate	99	0.98	0.80	0.81 (0.71-0.91)	0.72	0.92	85%
	Vigorous	334	1.00	0.89	0.97 (0.94-1.00)	0.44		
	ENMO							
	Sedentary	48	1.00	0.98	0.98 (0.96-1.00)	0.95		
	Moderate	68	0.98	0.80	0.81 (0.71-0.91)	0.75	0.93	87%
	Vigorous	216	0.90	0.92	0.96 (0.91-0.99)	0.46		
Back	**AC**							
	Sedentary	35	1.00	0.99	0.99 (0.98-1.00)	0.97		
	Moderate	98	0.92	0.81	0.83 (0.73-0.92)	0.67	0.90	83%
	Vigorous	391	1.00	0.91	0.97 (0.94-0.99)	0.47		
	MAD							
	Sedentary	35	1.00	0.98	0.98 (0.96-1.00)	0.95		
	Moderate	67	1.00	0.79	0.83 (0.73-0.92)	0.83	0.95	91%
	Vigorous	318	0.90	0.94	0.96 (0.93-0.99)	0.54		
	ENMO							
	Sedentary	45	1.00	0.98	0.99 (0.97-1.00)	0.94		
	Moderate	51	1.00	0.79	0.82 (0.73-0.92)	0.83	0.94	90%
	Vigorous	190	0.90	0.94	0.95 (0.92-0.99)	0.54		

Abbreviations: AC, activity counts; AUC, area under the curve; CI, confidence interval; ENMO, euclidean norm minus one; MAD, mean amplitude deviation; ROC, receiver operating characteristic.

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