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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 body mass 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

Obesity, and in particular, severe obesity [body mass index (IMC) > 35 kg m^{-2}] is a growing health problem worldwide [1], being associated with premature death, high morbidity and tremendous individual and societal costs [2]. The foundation of these patients' treatment lays on lifestyle changes, including healthy eating habits and increasing daily physical activity to promote a negative energy balance and excesses body fat loss. To adjust these two variables, clinicians face several difficulties, namely the lack of accurate instruments to assess patients' physical activity and energy expenditure (EE). Methods based on the self-perception, such as questionnaires, have been used for this purpose, but have low accuracy, especially in patients with obesity [3].

In the last decade, physical activity assessment by wearable devices, such as accelerometers, has been increasingly explored in several research fields and has shown potential for several health care applications. Accelerometers are affordable wearable devices that record linear accelerations resulting from body movement which can be translated

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into EE and physical activity intensity (PAI) classifications. This can be achieved by a calibration process [4]. Several calibration studies have been performed for different populations [5] because calibration results are only valid for populations with similar characteristics to those of the calibration sample, such as age (pediatric *vs* adults), body composition (normal weight *vs* obesity), physical fitness or health condition [6]. Obese people, especially those with severe obesity, have low resting metabolic rate (RMR) [7], high walking energetic cost [8] and low aerobic physical fitness [9] which hinders the use of accelerometer data for EE quantification and PAI classification based on calibration studies performed in normal weight samples. These particular characteristics imply that calibration studies in this population must be performed in order to develop specific regression equations that can accurately predict EE and develop specific cut-points to classify sedentary activity (SA) and PAI.

Although calibration studies for patients with obesity have already been developed by others [10,11], they evaluated only subjects with obesity class I (BMI 30–34.99 kg m^{-2}) or used uniaxial accelerometers, which are now outdated by the ubiquitous use of triaxial accelerometers. Moreover, calibration of accelerometer data in these studies was only performed for hip placement, which might be a limitation. The high hypodermal fat deposition in this region increases the noise in accelerometer recorded data [12], which might reduce the accuracy of the measurement compared to other waist positions such as lower back placement. Recent recommendations for harmonizing accelerometer research methodology [13,14] also suggest that calibration studies should swap arbitrary "activity counts" (AC) by new standard metrics based on raw acceleration, such as mean amplitude deviation (MAD) [15] and euclidean norm minus one (ENMO) [16]. Calibration results obtained with these new accelerometer metrics must not only prove to be valid, but also show an equal or superior accuracy compared with the well-established AC units [4].

The main purpose of this study was to develop regression equations that can accurately predict EE and cut-points to classify SA and PAI in severe obese people based on several metrics obtained from accelerometers placed at the hip and back. Three hypothesizes have been raised and were tested: i) accelerometer data collected in severe obese people allow to accurately estimate EE and to correctly classify SA and PAI; ii) raw acceleration metrics (MAD and ENMO) have similar accuracy compared with AC units; iii) back accelerometer placement has better accuracy compared with hip placement.

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 %; $\bar{X} \pm SD$) 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 (code: CES 192-14).

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 min. Second, the participant remained quiet in standing position for 3 min. 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. Although it was not possible to incorporate more daily life activities in the protocol, the tasks included reflect the main activities that characterize severe obese subjects' lifestyle [17]. Participation in other forms of physical activity (*e.g.*, run, jump) is less frequent in this population due to impaired mobility and low motor competence [18].

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 [19], as performed in this population in previous studies [20–23].

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 s of each protocol period were not included in the data analyses to avoid the incorporation of transitional movements. MAD [15] and ENMO [16] 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 (https://bit.ly/2pZ6UMK) [24], 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 ROC curve. RMR represented by VO_2

($ml \cdot kg^{-1} min^{-1}$) 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 > 6 MET – vigorous physical activity (VPA) [25]. 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 [26]. 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 define what is an acceptable error for the EE prediction, based on previous findings in this field [27], we considered an accurate prediction of those results that had a RMSE < 1.30 kcal min^{-1}.

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 [28]. Percent agreement from global classification was also calculated.

Data distribution normality was analyzed with the Shapiro-Wilk test before performing the remaining statistical analyses. 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 EE prediction equations developed for all accelerometer metrics from hip and back placement, their R^2 and accuracy indices. R^2 was similar among all regression equations, ranging from 0.86 to 0.90. The same was observed with the accuracy indices, with MAE ranging from 0.67 to 0.79 kcal min^{-1}, MAPE from approximately 14%–18% and RMSE from 0.88 to 1.02 kcal min^{-1}. Although only slightly, MAD was the accelerometer metric that showed the better accuracy indices, both for hip and back placement. All regression equations presented an acceptable error for the EE prediction (RMSE < 1.30 kcal min^{-1}).

Bland-Altman plots in Fig. 1 also confirmed the validity of the regression equations proposed, showing a good agreement between measured and predicted EE. In all analyses, the difference of the measured and predicted EE tends to be close to zero and within the LoA, revealing an irrelevant bias ($p > 0.05$), which ensures the absence of systematic under or overestimation of predicted EE. Additionally, non-proportional bias was detected ($p > 0.05$), which means that prediction error was similar across the entire range of EE assayed and was not influenced by measured magnitude.

Table 2 presents the cut-points developed for all accelerometer metrics from hip and back placement with their respective sensitivity, specificity and area under the ROC curve. In all analyses, sensitivity was higher than 0.88, specificity higher than 0.78 and the area under the ROC curve higher than 0.80. 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 classifications were categorized as almost perfect, MPA as substantial or almost perfect and VPA as moderate. All global classification agreements were categorized as almost perfect with a percent agreement above 83 %. Although the cut-points proposed to identify VPA presented limited accuracy, the cut-point sets developed have shown to be able to classify SA and PAI with a satisfactory level of accuracy.

Comparison among accelerometer metrics in each position and between them in hip and back placement showed no significant differences in accuracy of predicted EE and in classification agreement ($p > 0.05$). This shows that although there are slight differences in predicting accuracy among developed regression equations and cut-points, their ability to correctly predict EE and identify SA and PAI is similar.

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 PAI cut-points, with comparable classification agreement. These results suggest 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

Table 1
Regression equations, R^2 and accuracy indices.

Accelerometer		Regression equations	R^2	MAE	MAPE	RMSE
Placement	Metric					
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.

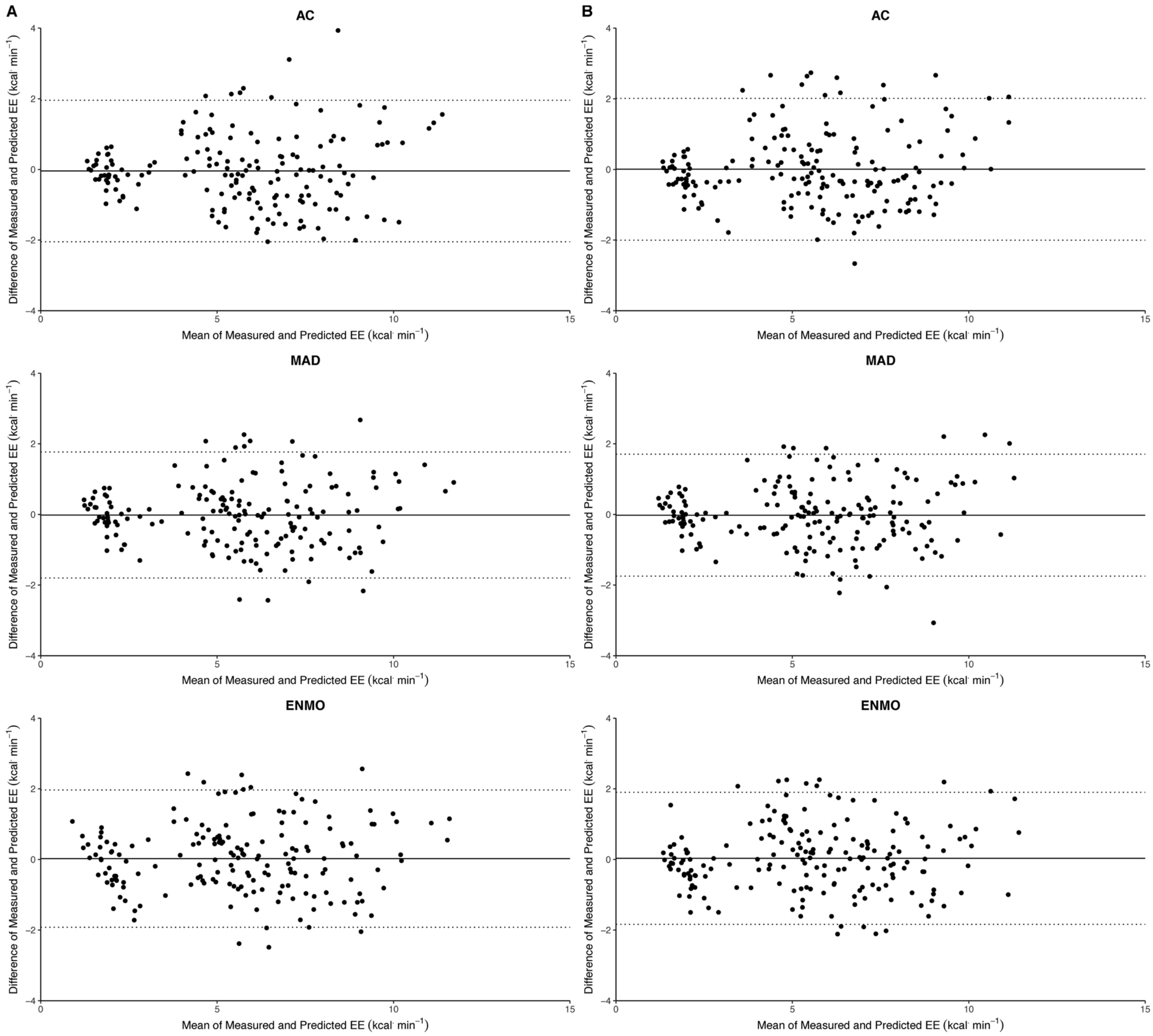

Fig. 1. Bland-Altman plots of measured and predicted EE in all accelerometer metrics from hip (left panel, A) and back (right panel, B) placement. Continuous thick lines show bias while dotted lines show upper and lower limits of agreement.
Abbreviations: ACactivity counts; ENMOeuclidean norm minus one; MADmean amplitude deviation.

should be adopted as reference [29]. 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 [30] or BMI level [12]. However, this does not seem to affect the results, such as predicted EE, if an adequate regression equation is applied to a specific placement [31]. 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 due to backpressure in a sitting position), we advocate that hip placement should continue to be used as a conventional position.

Results found with regression equations showed good accuracy and are in line with previous calibration studie [30,32]. Freedson et al. [32], who evaluated a non-obese sample in a treadmill protocol, have also shown that most of EE variance can be explained by AC and weight data, with a 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 [33]. 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. [11] 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 [5]. 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 [11]. 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 [34,35]. Cut-points for severe obese people are also mostly below when metrics were based on raw acceleration [30,36], although with a smaller difference.

Nowadays, due to its impact on health outcomes, one of the main

Table 2
Proposed cut-points and their classification agreement.

			ROC			Kappa		
		Cutpoint (5-s epochs)	Sensitivity	Specificity	AUC (95% CI)	Individual agreement	Global agreement	Percent agreement
Hip	**AC**							
	Sedentary	13	0.95	0.98	0.99 (0.97-1.00)	0.91	0.94	91%
	Moderate	130	0.98	0.81	0.83 (0.73-0.93)	0.81		
	Vigorous	463	0.89	0.96	0.96 (0.92-1.00)	0.55		
	MAD							
	Sedentary	8	0.97	0.98	0.98 (0.96-1.00)	0.93	0.92	86%
	Moderate	99	0.98	0.80	0.81 (0.71-0.91)	0.72		
	Vigorous	334	1.00	0.89	0.97 (0.94-1.00)	0.44		
	ENMO							
	Sedentary	37	0.95	0.98	0.98 (0.96-1.00)	0.92	0.92	87%
	Moderate	68	0.98	0.80	0.81 (0.71-0.91)	0.75		
	Vigorous	216	0.90	0.92	0.96 (0.91-0.99)	0.46		
Back	**AC**							
	Sedentary	10	0.95	0.99	0.99 (0.98-1.00)	0.94	0.90	83%
	Moderate	98	0.92	0.81	0.83 (0.73-0.92)	0.67		
	Vigorous	391	1.00	0.91	0.97 (0.94-0.99)	0.47		
	MAD							
	Sedentary	7	0.95	0.98	0.98 (0.96-1.00)	0.90	0.94	90%
	Moderate	67	1.00	0.79	0.83 (0.73-0.92)	0.83		
	Vigorous	318	0.90	0.94	0.96 (0.93-0.99)	0.54		
	ENMO							
	Sedentary	34	0.98	0.98	0.99 (0.97-1.00)	0.92	0.95	91%
	Moderate	51	1.00	0.79	0.82 (0.73-0.92)	0.83		
	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.

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 1.0–1.5 METs in almost all participants. Therefore, what was measured was SA [25] and not sedentary behavior which does not include standing position tasks [37]. 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 [38,39]. 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.

Class II-III obesity has increased alarmingly in the last years. Accurate measurements are essential to understand the true physical activity levels of these patients and to monitor the efficacy of interventions to increase daily physical activity levels. One of the most common concerns in this clinical context is the accurate determination of the daily energy balance [40]. Our regression equations were specifically developed and validated for patients with severe obesity and will allow an accurate quantification of daily EE. This knowledge can be used as reference to prescribe calorie-restricted diets to obtain the desired daily energy deficit and therefore to promote an adequate excess body mass loss. Knowing more accurately the amount of time in each PAI level is also of interest as it allows to determine the adherence of these patients to general health physical activity guidelines and the risks incurred by being in sedentary time [41,42]. Our cut-points have shown a good level of accuracy allowing a trustful characterization of physical activity levels in patients with severe obesity.

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 [17], our protocol did not include sufficient activities that have fully represented severe obese people lifestyle [4,6]. Second, a different sample for model validation was not available, thus a dataset created from LOOCV method was used as recommended for this situation [33].

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.

Declaration of Competing Interest

None.

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References

[1] NCD Risk Factor Collaboration, Trends in adult body-mass index in 200 countries from 1975 to 2014: a pooled analysis of 1698 population-based measurement studies with 19.2 million participants, Lancet 387 (10026) (2016) 1377–1396.

[2] T. von Lengerke, C. Krauth, Economic costs of adult obesity: a review of recent European studies with a focus on subgroup-specific costs, Maturitas 69 (3) (2011) 220–229.

[3] A. Lipert, A. Jegier, Comparison of different physical activity measurement methods in adults aged 45 to 64 years under free-living conditions, Clin. J. Sport Med. 27 (4) (2017) 400–408.

[4] D.R. Bassett Jr, A. Rowlands, S.G. Trost, Calibration and validation of wearable monitors, Med. Sci. Sports Exerc. 44 (1 Suppl 1) (2012) S32–8.

[5] J.H. Migueles, C. Cadenas-Sanchez, U. Ekelund, C. Delisle Nystrom, J. Mora-Gonzalez, M. Lof, et al., Accelerometer data collection and processing criteria to assess physical activity and other outcomes: a systematic review and practical considerations, Sports Med. 47 (9) (2017) 1821–1845.

[6] G.J. Welk, Principles of design and analyses for the calibration of accelerometry-based activity monitors, Med. Sci. Sports Exerc. 37 (11 Suppl) (2005) S501–11.

[7] N.M. Byrne, A.P. Hills, G.R. Hunter, R.L. Weinsier, Y. Schutz, Metabolic equivalent: one size does not fit all, J. Appl. Physiol. (1985) 99 (3) (2005) 1112–1119.

[8] R.C. Browning, E.A. Baker, J.A. Herron, R. Kram, Effects of obesity and sex on the energetic cost and preferred speed of walking, J. Appl. Physiol. (1985) 100 (2) (2006) 390–398.

[9] S.A. de Souza, J. Faintuch, A.F. Sant'anna, Effect of weight loss on aerobic capacity in patients with severe obesity before and after bariatric surgery, Obes. Surg. 20 (7) (2010) 871–875.

[10] C.C.F. Howe, H.J. Moir, C. Easton, Classification of physical activity cut-points and the estimation of energy expenditure during walking using the GT3X+ accelerometer in overweight and obese adults, Meas. Phys. Educ. Exerc. Sci. 21 (3) (2017) 127–133.

[11] E. Aadland, S.A. Anderssen, Treadmill calibration of the actigraph GT1M in young-to-Middle-Aged obese-to-Severely obese subjects, J. Obes. 2012 (2012) 318176.

[12] Y. Feito, D.R. Bassett, B. Tyo, D.L. Thompson, Effects of body mass index and tilt angle on output of two wearable activity monitors, Med. Sci. Sports Exerc. 43 (5) (2011) 861–866.

[13] K. Wijndaele, K. Westgate, S.K. Stephens, S.N. Blair, F.C. Bull, S.F. Chastin, et al., Utilization and harmonization of adult accelerometry data: review and expert consensus, Med. Sci. Sports Exerc. 47 (10) (2015) 2129–2139.

[14] V.T. van Hees, K. Thaler-Kall, K.H. Wolf, J.C. Brond, A. Bonomi, M. Schulze, et al., Challenges and opportunities for harmonizing research methodology: raw accelerometry, Methods Inf. Med. 55 (6) (2016) 525–532.

[15] H. Vaha-Ypya, T. Vasankari, P. Husu, J. Suni, H. Sievanen, A universal, accurate intensity-based classification of different physical activities using raw data of accelerometer, Clin. Physiol. Funct. Imaging 35 (1) (2015) 64–70.

[16] V.T. van Hees, L. Gorzelniak, E.C. Dean Leon, M. Eder, M. Pias, S. Taherian, et al., Separating movement and gravity components in an acceleration signal and implications for the assessment of human daily physical activity, PLoS One 8 (4) (2013) e61691.

[17] B.H. de Rooij, J.D. van der Berg, C.J. van der Kallen, M.T. Schram, H.H. Savelberg, N.C. Schaper, et al., Physical activity and sedentary behavior in metabolically healthy versus unhealthy obese and non-obese individuals - the maastricht study, PLoS One 11 (5) (2016) e0154358.

[18] W.C. King, D.S. Bond, The importance of preoperative and postoperative physical activity counseling in bariatric surgery, Exerc. Sport Sci. Rev. 41 (1) (2013) 26–35.

[19] J.B. Weir, New methods for calculating metabolic rate with special reference to protein metabolism, J. Physiol. (Paris) 109 (1–2) (1949) 1–9.

[20] B.A.P. de Oliveira, C.F. Nicoletti, C.C. de Oliveira, M.A.S. Pinhel, D.C.G. Quinhoneiro, N.Y. Noronha, et al., A new resting metabolic rate equation for women with class III obesity, Nutrition 49 (2018) 1–6.

[21] L.M. Horie, M.C. Gonzalez, R.S. Torrinhas, I. Cecconello, D.L. Waitzberg, New specific equation to estimate resting energy expenditure in severely obese patients, Obesity (Silver Spring) 19 (5) (2011) 1090–1094.

[22] A.L. Kee, E. Isenring, I. Hickman, A. Vivanti, Resting energy expenditure of morbidly obese patients using indirect calorimetry: a systematic review, Obes. Rev. 13 (9) (2012) 753–765.

[23] M. Marra, I. Cioffi, R. Sammarco, C. Montagnese, M. Naccarato, V. Amato, et al., Prediction and evaluation of resting energy expenditure in a large group of obese outpatients, Int. J. Obes. (Lond.) 41 (5) (2017) 697–705.

[24] L. Veras, verasls/EE_PAI_ACC_obese: Accelerometry Calibration in People with Class II-III Obesity: Energy Expenditure Prediction and Physical Activity Intensity Identification (Version v1.0.0). Zenodo, (2019).

[25] Committee PAGA, Physical Activity Guidelines Advisory Committee Scientific Report, U.S. Department of Health and Human Services, Washington, DC, 2018, pp. C7–8.

[26] D. Giavarina, Understanding Bland Altman analysis, Biochem. Med. (Zagreb) 25 (2) (2015) 141–151.

[27] K. Lyden, S.L. Kozey, J.W. Staudenmeyer, P.S. Freedson, A comprehensive evaluation of commonly used accelerometer energy expenditure and MET prediction equations, Eur. J. Appl. Physiol. 111 (2) (2011) 187–201.

[28] J.R. Landis, G.G. Koch, The measurement of observer agreement for categorical data, Biometrics 33 (1) (1977) 159–174.

[29] M. deAlmeida Mendes, I.C.M. da Silva, V.V. Ramires, F.F. Reichert, R.C. Martins, E. Tomasi, Calibration of raw accelerometer data to measure physical activity: a systematic review, Gait Posture 61 (2018) 98–110.

[30] H. Vaha-Ypya, T. Vasankari, P. Husu, A. Manttari, T. Vuorimaa, J. Suni, et al., Validation of cut-points for evaluating the intensity of physical activity with accelerometry-based mean amplitude deviation (MAD), PLoS One 10 (8) (2015) e0134813.

[31] A. Yngve, A. Nilsson, M. Sjostrom, U. Ekelund, Effect of monitor placement and of activity setting on the MTI accelerometer output, Med. Sci. Sports Exerc. 35 (2) (2003) 320–326.

[32] P.S. Freedson, E. Melanson, J. Sirard, Calibration of the computer science and applications, Inc. Accelerometer, Med. Sci. Sports Exerc. 30 (5) (1998) 777–781.

[33] J. Staudenmayer, W. Zhu, D.J. Catellier, Statistical considerations in the analysis of accelerometry-based activity monitor data, Med. Sci. Sports Exerc. 44 (1 Suppl 1) (2012) S61–7.

[34] J.E. Sasaki, D. John, P.S. Freedson, Validation and comparison of ActiGraph activity monitors, J. Sci. Med. Sport 14 (5) (2011) 411–416.

[35] A. Santos-Lozano, F. Santin-Medeiros, G. Cardon, G. Torres-Luque, R. Bailon, C. Bergmeir, et al., Actigraph GT3X: validation and determination of physical activity intensity cut points, Int. J. Sports Med. 34 (11) (2013) 975–982.

[36] M. Hildebrand, V.T. VANH, B.H. Hansen, U. Ekelund, Age group comparability of raw accelerometer output from wrist- and hip-worn monitors, Med. Sci. Sports Exerc. 46 (9) (2014) 1816–1824.

[37] M.S. Tremblay, S. Aubert, J.D. Barnes, T.J. Saunders, V. Carson, A.E. Latimer-Cheung, et al., Sedentary Behavior Research Network (SBRN) - terminology consensus project process and outcome, Int. J. Behav. Nutr. Phys. Act. 14 (1) (2017) 75.

[38] J. Bai, C. Di, L. Xiao, K.R. Evenson, A.Z. LaCroix, C.M. Crainiceanu, et al., An activity index for raw accelerometry data and its comparison with other activity metrics, PLoS One 11 (8) (2016) e0160644.

[39] K. Bakrania, T. Yates, A.V. Rowlands, D.W. Esliger, S. Bunnewell, J. Sanders, et al., Intensity thresholds on raw acceleration data: euclidean norm minus one (ENMO) and mean amplitude deviation (MAD) approaches, PLoS One 11 (10) (2016) e0164045.

[40] T. Psota, K.Y. Chen, Measuring energy expenditure in clinical populations: rewards and challenges, Eur. J. Clin. Nutr. 67 (5) (2013) 436–442.

[41] World Health Organization, Guidelines Approved by the Guidelines Review Committee. Global Recommendations on Physical Activity for Health, World Health Organization. Copyright (c) World Health Organization, Geneva, 2010, p. 8.

[42] J.E. Donnelly, S.N. Blair, J.M. Jakicic, M.M. Manore, J.W. Rankin, B.K. Smith, American College of Sports Medicine Position Stand. Appropriate physical activity intervention strategies for weight loss and prevention of weight regain for adults, Med. Sci. Sports Exerc. 41 (2) (2009) 459–471.