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Development and validation of an activPAL accelerometry count-based model of physical activity intensity in adults

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ABSTRACT

The activPAL linear cadence-metabolic equivalents (METs) equation poorly estimates activity intensity. The magnitude of acceleration in three directional planes may be a superior predictor of activity intensity than stepping cadence, with accelerometry count thresholds developed in children/adolescent populations. We extracted the proprietary accelerometer-derived information to develop a counts-METs model and cross-validates it in laboratory and free-living conditions. Forty adults (25±6 years) wore an activPAL during a 7-stage progressive treadmill protocol (criterion: indirect calorimetry). Tri-axial accelerometry-derived activity counts (vector magnitude) and METs data from a subset of participants (n = 20) were modelled (R^2=0.76) and the regression equation evaluated in the remaining participants (n = 20). Thirty-two of these participants wore the activPAL during free-living conditions (n = 192-d; criterion: PiezoRxD monitor). The absolute percent error of the counts-METs model in the laboratory cross-validation was 18±13%, with equivalence testing determinining equivalent MET values to indirect calorimetry during the slowest (1.5 mph) and fastest (4.0-4.5 mph) stages. In free-living conditions, the model accurately quantified light- and moderate-intensity physical activity but underestimated vigorous-intensity activity (6.5±11.3 vs. 5.5±20.8 mins/day; $p < 0.001$). We developed and present a data analysis method using the activPAL tri-axial accelerometry counts to improve estimations of physical activity intensity in controlled laboratory settings and uncontrolled free-living settings.

1. Introduction

The thigh worn activPAL monitor is a commonly used objective measure of habitual physical activity and posture [1]. However, the activPAL poorly estimates intensity-related physical activity [2–4], which is particularly problematic given that this is a major component of international activity guidelines [5]. The activPAL estimates intensity by linearly relating stepping cadence and metabolic equivalents of task (METs), whereby moderate- (MPA) and vigorous-intensity physical activity (VPA) are achieved at ~75 and ~212 steps•min^{-1}, respectively [6]. Using these default stepping cadence thresholds, we demonstrated that the activPAL misclassified light-intensity physical activity (LPA) as MPA, and was completely unable to detect VPA [6,7]. Our laboratory has proposed an alternative, curvilinear cadence-METs equation that better predicted physical activity intensity than the default linear equation [7]. Despite being a clear improvement (mean absolute percent error: ~15%), the model still underpredicted METs at the fastest walking stage and VPA in free-living conditions (i.e., the setting where the activPAL is frequently utilized) [7]. While stepping cadence is intuitively easy to understand, activity monitors can also provide detailed information regarding the magnitude of accelerations in various directional planes. Herein, physical activity can be determined using a variety of data processing strategies that include the raw accelerometry profile (e.g., Euclidean Norm Minus One) or proprietary filtered count-based processing methods (i.e., accelerometry counts) [8]. The use of acceleration, versus step counts, may be a superior means of quantifying physical activity intensity. In support of this hypothesis, Harrington et al. (2011) identified that the development of a counts-METs model may be more useful than a cadence-METs model for predicting activity intensity. Despite our previous efforts [6,7], there remains a need to further investigate potential analytical strategies to improve the measurement of activPAL-derived physical activity intensity, particularly VPA that is completely unachievable via its default settings.

The activPAL incorporates uniaxial (vertical axis only in older models [original activPAL]) or tri-axial (activPAL version 3 and later)

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accelerometers, which can export summed accelerometry counts in 15s epochs. Previous studies using vertical, uniaxial versions have developed and cross-validated count-based thresholds to determine physical activity intensity in children [9] and adolescent [10] populations. However, these thresholds demonstrated poor concurrent validity when evaluated in adults relative to the waist-worn ActiGraph [4], indicating that these thresholds cannot be extrapolated to this population. Current activPAL models (version 3 and 4) permit the determination of a resultant vector magnitude (VM) by using the acceleration profile across all 3 axes (vertical, horizontal, forward). Importantly, studies have been conducted equating activity counts to physical activity intensity in waist-worn monitors, as previously reported [4,11]. However, such activity count values are not comparable between different devices, particularly when worn on different locations (thigh versus hip) that exhibit unique acceleration profiles during movement [10].

The purpose of this study was to develop and cross-validate a model that predicts METs from activity counts using VM (tri-axial) accelerometry counts in adults. Since the activPAL is typically utilized in free-living conditions to determine habitual activity [1], we also determined the accuracy of these count-based intensity thresholds to determine free-living intensity-related physical activity versus a previously validated criterion measure (i.e., PiezoRxD) [12–14].

2. Methods

2.1. Participants

Forty adults provided informed consent to participate in the study. A random sub-sample (n = 20) was used to develop the counts-METs model, which was cross-validated against the other 20 participants. The group allocation for the random sub-sample was determined using a random list generator function in excel (Microsoft, Washington, USA). Participant characteristics are presented in Table 1. Ethics approval was granted by the Dalhousie University Health Sciences Research Ethics Board. Participants abstained from alcohol and VPA for 24-h, as well as caffeinated products for 12-h prior to their laboratory visit. Each participant arrived well-rested, well-hydrated, avoided large meals, and consumed a light meal ~2-h beforehand. The laboratory Development and Cross-Validation sample size was based on previous studies of a similar nature in children (n = 18 per group) [9] and adolescents (n = 15 per group) [10]. The validity of activPAL step counts and the criterion measure of physical activity intensity (indirect calorimetry and PiezoRxD data) have been presented [7]. However, that study [7] examined the relationship between cadence-METS and did not present any activPAL accelerometry count data. The analyses and purpose in the present study are unique and used to answer an independent research question.

Table 1
Participant characteristics for the Pooled Sample, as well as the Development and Cross-Validation groups.

	Pooled Sample (n = 40)	Development(n = 20)	Cross-Validation (n = 20)
Age (years)	25 ± 6	25 ± 5	25 ± 6
Sex (Male, Female)	16, 24	7, 13	9, 11
Height (cm)	170 ± 9	170 ± 9	169 ± 8
Weight (kg)	68 ± 16	64 ± 16	72 ± 15
Body Mass Index ($kg \bullet m^{-2}$)	23.3 ± 4.1	21.6 ± 3.4	25.0 ± 4.1*
Resting VO_2 ($ml \bullet kg^{-1} \bullet min^{-1}$)	3.60 ± 0.50	3.74 ± 0.50	3.47 ± 0.48

Data are presented as means ± standard deviation. Body mass index was larger in the Cross-Validation sample (p=0.01), all other variables were similar between groups (P>0.09).

2.2. Laboratory protocol

Height and weight (to the nearest 0.5-cm and 0.1-kg, respectively) were measured using a calibrated stadiometer (Health-O-Meter, McCook, IL, USA). The volume rate of oxygen consumption (VO_2) was measured during a 15-min supine rest period and a treadmill walking protocol (see below) via a calibrated mixing chamber-based metabolic cart (TrueOne 2400, Parvo Medics, Sandy, UT, USA) connected in series to an 800 $L \bullet min^{-1}$ heated pneumotachometer. The last 5-min of the supine rest period was used to calculate resting VO_2. Participants were equipped with an activPAL inclinometer (activPAL3, PAL Technologies Ltd, Glasgow, UK) that was centered on the midpoint of their right thigh via transparent medical dressing (Tegaderm, 3M, Ontario, Canada). A wireless heart rate monitor (Polar, H9, Lachine, QC, Canada) was also secured across their sternum.

The treadmill walking protocol was based on previous studies [2,6,15-16] and consisted of seven, 6-min stages interspersed by 4-min of passive recovery (i.e., straddling the treadmill belt). The treadmill speeds for each stage progressively increased as follows: 1.5, 2.0, 2.5, 3.0, 3.5, 4.0, and 4.5 $miles \bullet h^{-1}$ at 0% grade. The protocol was terminated if participants reached 85% of their age-estimated maximum heart rate (220 - age) or started jogging/running. A cool down period followed the end of the protocol to allow heart rate to gradually return to resting values.

2.3. Free-living protocol

Following the treadmill walking protocol, 32 participants wore an activPAL on their right thigh and a PiezoRxD on their right hip for an additional 7-d of habitual activity. Eight participants opted out of wearing the devices during the free-living condition. The PiezoRxD was programmed to use step rate thresholds to determine time spent in LPA, MPA and VPA. The standard threshold settings for a 1.70 m person were 100 $steps \bullet min^{-1}$ for MPA and 130 $steps \bullet min^{-1}$ for VPA [12,13]. Adjustments of 5 $steps \bullet min^{-1}$ were incorporated for each 0.1 m increase (-5 $steps \bullet min^{-1}$) or decrease (+5 $steps \bullet min^{-1}$) in height from 1.70 m [13,16]. Participants self-reported PiezoRxD wear time and indicated when the device was removed (swimming, sleeping, etc.), which was confirmed through the LogYourSteps online platform. Participants self-reported their sleep times to accommodate analysis of the activPAL data and ensured that only data when both the activPAL and PiezoRxD were worn were analyzed.

2.4. Relationship between accelerometry counts and physical activity intensity

In the Development sample model (n = 20), 134 total observations were collected from the treadmill protocol. Participant-level plots of METs as a function of accelerometry counts indicated a non-linear relationship. Therefore, a number of candidate models were explored. Using VM activity counts as the predictor variable and METs as the outcome variable, linear (counts), quadratic ($counts^2$), cubic ($counts^3$) and logarithmic (e^{counts}) relationships were evaluated. The amount of variance explained by each model (i.e., R^2 value) was used as the primary criterion to determine the model that best described the relationships between activity counts and METs. The logarithmic model exhibited the largest R^2 value (R^2 = 0.76; Figure 1). The indirect calorimetry-derived MET values and the average activity counts per 15-s epoch are presented for this Development sample in Supplemental Table 1.

2.5. Cross-validation in laboratory and free-living conditions

The VM model determined in the Development sample was tested in the laboratory Cross-Validation sample (n = 20) and in the 32 participants who wore the device during free-living conditions (n = 17 in

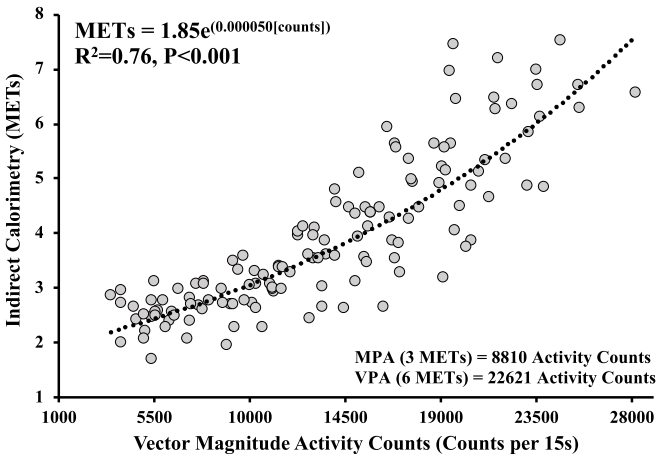

Figure 1. Scatterplot depicting the logarithmic relationship between indirect calorimetry-derived metabolic equivalents of task (METs) versus the 15-s averaged vector magnitude activity counts from the Development group (n = 20). Each data point represents 1 laboratory treadmill stage (134 total observations). The activity count thresholds that corresponded to absolute moderate (3 METs) and vigorous (6 METs) intensity physical activity are presented.

Development and n = 15 in Cross-Validation). For the laboratory cross-validation, the activity counts determined for each treadmill stage were inputted into the developed model and the calculated MET value was compared to that derived via indirect calorimetry.

The PiezoRxD provides time spent in LPA, MPA and VPA, and not specific MET values. Therefore, activity count thresholds that corresponded to 3 METs (10.5 ml/kg/min) and 6 METs (21 ml/kg/min) were determined based on the Development sample (Figure 1). Daily time spent within these VM activity count thresholds were determined and compared to the PiezoRxD.

2.6. Data analysis

The activPAL data were downloaded from the device using the PAL Software Suite (Version 7, PAL Technologies Ltd, Glasgow, UK). This software outputs proprietary acceleration counts in 15-s epochs, including the magnitude of counts in the vertical, horizontal, and forward axes. The resultant VM incorporates all 3 planes (X, Y, Z) and was calculated as the square root of the sum of squares (vertical^2 + horizontal^2 + forward^2)$^{1/2}$.

Laboratory Data Analysis: All VO_2 data were averaged over 15-s intervals. A standard relative VO_2 of 3.5 mL•kg^{-1}•min^{-1} was used to define 1 MET [17]. During the treadmill protocol, all MET values were calculated by dividing the averaged VO_2 data by 3.5 mL•kg^{-1}•min^{-1}. Importantly, the average resting relative VO_2 for all participants in this study (3.6±0.5 mL•kg^{-1}•min^{-1}) was similar to this standardized value.

During the treadmill walking protocol, 13 participants were unable to complete stage 7 (n = 7 Development, n = 6 Cross-Validation). As such, stage 7 data were presented for 27 participants only. Steady-state indirect calorimetry-derived METs and accelerometry counts in each axis were averaged over the final 4-min of each stage..

Free-Living Data Analysis: A total of 192-d of simultaneous PiezoRxD and activPAL habitual activity data were used for analysis. Time spent in LPA, MPA, and VPA were estimated separately using the PiezoRxD and the VM count thresholds. Time spent engaged in intensity-related physical activity for the activPAL was obtained from the 15-s epoch file. The PiezoRxD stores accumulated data for steps, LPA (i.e., total physical activity – MVPA), MPA, and VPA. The PiezoRxD sums these data into 10-min bouts.

2.7. Statistical analyses

All statistical analyses were conducted in accordance with standardized reporting guidelines for physical activity monitor validation studies [18]. All dependent variables were assessed for normality using a Shapiro-Wilk test, with METs confirmed non-normal and logarithmically transformed, which resulted in these data being normally distributed (with the exception of free-living LPA, MPA and VPA that was not normally distributed after log transformation). These data were then back transformed for presentation. Mean MET values during the laboratory condition and time spent in each intensity category were compared via a repeated measures analysis of variance (RM-ANOVA) and Friedman's ANOVA, respectively. For RM-ANOVA, the variance of differences was assessed using Mauchly's test of sphericity and the Greenhouse-Geisser correction factor to the degrees of freedom used if assumptions of sphericity were violated. Bonferroni *post-hoc* testing was used for pairwise comparisons if significant interactions were identified. For significant Friedman's ANOVA, *post-hoc* testing was performed via the Wilcoxon signed rank test.

Absolute error was calculated to compare criterion- versus VM-derived METs for each treadmill stage, as well as intensity categories for the free-living condition. Absolute mean error was chosen over absolute percent error for free-living comparisons because some measures can exhibit artificially large percent errors but report relatively similar values. (e.g., 2 minutes vs 1 minute of VPA).

Equivalence testing was conducted with an equivalence zone set at ±10% of the mean indirect calorimetry-derived METs and ±20% of the PiezoRxD-derived METs. Ninety percent confidence intervals were used for the mean estimated METs from the activPAL count thresholds. These relatively conservative criteria were used because the laboratory condition represents a more controlled environment, whereas the free-living condition is less controlled [6,18]. Specific guidelines on the magnitude of equivalence zones are unclear.

The Bland-Altman method of differences was used to compare predicted METs (laboratory) and time spent in each physical activity intensity (free-living) versus the corresponding criterion measures. These analyses provided the mean difference and limits of agreement (1.96 ± standard deviation) and determined whether a fixed bias (i.e., mean difference not equal to '0'; via one-sample t-test to zero) and/or a proportional bias (i.e., amount of difference is dependent on the magnitude of the average values [difference-average slope does not equal '0') existed via outcome difference versus average outcome regression model [19].

All statistical analyses were completed in SPSS (Version 26.0. IBM Corp., Armonk, NY). Data were reported as means ± standard deviations, and statistical significance was accepted as $p < 0.05$.

3. Results

3.1. Laboratory cross-validation

The Cross-Validation group had a larger body mass index than the Development sample (p = 0.01; see Table 1). The activity counts for each treadmill stage and Bland-Altman results are presented in Supplemental Tables 2 and 3, respectively. Based on the RM-ANOVA, the activity counts-derived METs were not different to indirect calorimetry-derived METs for Stage 1 (1-mph) and Stages 5-7 (3.5- to 4.5-mph) but overestimated METs during Stages 2-4 (2.0- to 3.0-mph) (Table 2). Based on the equivalence testing, the VM-based METs was statistically equivalent to indirect calorimetry during the slowest (1.5 mph) and fastest stages (4.0-4.5 mph). Overall, the VM-calculated METs exhibited a small negative fixed bias (underprediction) but not a proportional bias (Supplemental Table 3). The predicted METs were strongly correlated to indirect calorimetry-determined METs (R^2 = 0.68) in the Cross-Validation sample (see Figure 2).

Table 2
Comparison of metabolic equivalents of task (METs), absolute percent error for METs and equivalence zones at each treadmill stage between indirect calorimetry- and vector magnitude activity counts-derived METs.

Metabolic Equivalents of Task			Absolute % Error	Equivalence Zone	
Stage (mph)	Indirect Calorimetry	Vector Magnitude	IC-VM	Indirect Calorimetry	Vector Magnitude
Stage 1 (1.5)	2.4 ± 0.2	2.5 ± 0.2	13 ± 11	2.14-2.61	2.42-2.58#
Stage 2 (2.0)	2.6 ± 0.2	3.0 ± 0.3*	19 ± 15	2.32-2.84	2.87-3.11
Stage 3 (2.5)	2.9 ± 0.3	3.5 ± 0.5*	23 ± 17	2.65-3.24	3.34-3.69
Stage 4 (3.0)	3.5 ± 0.4	4.0 ± 0.5*	22 ± 14	3.15-3.85	3.81-4.22
Stage 5 (3.5)	4.2 ± 0.5	4.5 ± 0.6	19 ± 11	3.77-4.61	4.26-4.74
Stage 6 (4.0)	5.3 ± 0.7	5.2 ± 0.8	16 ± 10	4.73-5.78	4.89-5.52#
Stage 7 (4.5)	6.4 ± 0.6	6.1 ± 0.7	12 ± 10	5.73-7.01	5.73-6.43#
Overall	3.8 ± 1.4	4.0 ± 1.2	18 ± 13	3.38-4.13	3.84-4.19

Data are presented as means ± standard deviations. IC, indirect calorimetry; VM, vector magnitude. *, $p < 0.05$ versus indirect calorimetry-derived METs within same stage

#, within equivalence zone of indirect calorimetry. METs from each stage were analyzed via a [Method × Stage] repeated-measures analysis of variance with Bonferroni *post-hoc* testing. METs progressively increased with treadmill speed for all analytic approaches. Equivalent zones were set at ±10% of mean METs for indirect calorimetry (criterion) and at 90% confidence intervals of mean METs for the VM-determined METs.

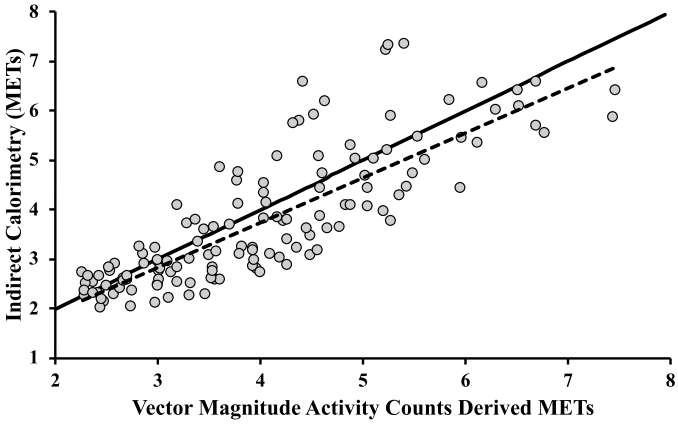

Figure 2. Scatterplot depicting the relationship between metabolic equivalents of task (METs) derived via indirect calorimetry versus the logarithmic counts-METs equation from the vector magnitude data in the Cross-Validation group ($n = 20$). Each data point represents 1 laboratory treadmill stage (133 observations total). Perfect agreement is signified by the solid black line versus the regression (dashed). METs estimated from the vector magnitude 15-s epochs (R^2=0.68; $p < 0.001$) were strongly correlated to METs measured via indirect calorimetry.

3.2. Free-living validation

The VM count thresholds resulted in LPA and MPA values statistically equivalent to the criterion measure (Table 3). Compared to the PiezoRxD, the VM estimated less time in VPA (both, $p < 0.001$). Furthermore, the 90% confidence intervals for the VM (3.0-8.0 mins•day^{-1}) did not fall within the ±20% equivalence zone for indirect calorimetry (5.2-7.8 mins•day^{-1}).

Table 3
Comparison of time spent in different physical activity intensities during the free-living condition.

	Time(mins•day^{-1})		Absolute Error (mins•day^{-1})	Equivalence Zone	
Intensity	PiezoRxD	Vector Magnitude	PRX-VM	PiezoRxD	Vector Magnitude
LPA	62.0 ± 27.5	63.4 ± 33.1	20.9 ± 15.0	49.6-74.4	59.4-67.3#
MPA	36.7 ± 20.4	33.0 ± 29.4	14.5 ± 16.0	29.3-44.1	29.5-36.5#
VPA	6.5 ± 11.3	5.5 ± 20.8*	7.1 ± 15.1	5.2-7.8	3.0-8.0

Data presented as means ± standard deviations. N = 32 (20 females) resulted in 192-d (total observations). LPA, light-intensity physical activity; MPA, moderate-intensity physical activity; VPA, vigorous-intensity physical activity; *, $p < 0.05$ versus PiezoRxD

#, within equivalence zone of PiezoRxD. Time spent in LPA, MPA, and VPA were analyzed via Friedman's analysis of variance with *post-hoc* Wilcoxon signed rank test. Equivalent zones were set at ±20% of mean PiezoRxD data (criterion) and at 90% confidence intervals of the vector magnitude. Vector magnitude count thresholds for MPA and VPA were 8810 and 22621 counts per 15-s epoch, respectively.

4. Discussion

The purpose of this study was to develop an activity counts-METs activPAL equation and determine its validity in estimating intensity-related physical activity during laboratory (versus indirect calorimetry) and free-living (versus PiezoRxD) conditions. Using the VM (triaxial accelerometry), we demonstrate that the accelerometry output may be used to improve upon default settings in determining intensity-related physical activity in both controlled and uncontrolled environments.

It is well established that the default activPAL stepping cadence-based settings poorly estimates physical activity intensity. The default settings recorded 0 seconds of VPA across 192-d (or 4608 h) of habitual wear time [7] due to the linear cadence-METs equation requiring a cadence of 212 steps•min^{-1} to reach the minimum threshold of VPA (i.e., 6 METs) [2,6,20]. Clearly, the data analysis strategy implemented improved the measurement of physical activity intensity compared to default settings that rely on a linear cadence-METs relationship, with values reflective of indirect calorimetry (Figure 2) and relatively low mean absolute percent errors of ~18%. While the proposed count-based analysis introduced in this study was not statistically equivalent to indirect calorimetry in every stepping stage, it nevertheless made the detection of VPA in both laboratory and free-living settings possible.

We have previously presented an alternative curvilinear, height-adjusted cadence-METs equation that also improved the ability of the device to measure activity intensity [7]. However, the possibility of using accelerometry counts was not investigated, despite these methods being very popular for waist-worn devices [4,11]. The results of the present study are similar to our previous cadence-based study [7] in that the mean absolute percent errors across all treadmill stages were ~13-23%, and that LPA and MPA, but not VPA, were statistically equivalent to the criterion measure during free-living [7]. A notable difference between the curvilinear cadence-METs and counts-METs models is that using cadence better predicted METs during the slow-middle speed treadmill walking stages (Stages 2.0-3.5 mph) [7], whereas the count-based method was better at the faster treadmill stages (Stages 4.0-4.5 mph). While outperforming the default linear

cadence-METs model, the proposed curvilinear counts-based model performs similar to, but not better than our previous curvilinear cadence-METs model. The counts-based model likely performed better during the faster walking stages as it considers the acceleration profile in multiple axis (i.e., horizontal, vertical, forward) whereas the cadence-based model relies solely on steps. With faster walking speeds, is an increase in step length (1.5 mph: ~0.5 meters/step, 4.5 mph: ~0.9 meters/step) [15]. Activity intensity at faster walking speeds appears to be better identified using accelerometry counts, as stepping cadence (i.e., steps/min) does not consider the length of the step, which could influence the metabolic demand of walking. In contrast, the curvilinear cadence may be superior to accelerometry counts during slower walking speeds (~100 steps/min) that correspond to the absolute threshold of moderate-intensity physical activity. Regardless, both methods were similarly accurate in free-living settings, where the activPAL is frequently used and quantified using time spent in each intensity category rather than specific MET values. Caution should be exercised when interpreting activPAL physical activity intensity data when the default settings are used. Our proposed cadence-based and count-based models make it possible for researchers to analyze their data *post-hoc* to more accurately measure intensity-related physical activity.

The objective of the present study aligns with recommendation by Harrington et al. [11] to investigate count-based analysis strategies to better predict intensity using the activPAL. The use of accelerometry counts to measure physical activity has been widely implemented in other device such as the ActiGraph [4,11], but count-based thresholds are not comparable between activity monitors [10]. This strategy, using the vertical axis only of older activPAL device, has been implemented in children (MVPA: >1418 counts per 15s epoch) [9] and adolescents (MPA: 2997 counts per 15s epoch; VPA: 8229 counts per 15s epoch) [10] who have a different counts-METs relationship than adults, as evident by the thresholds presented in Figure 1. This is corroborated by the results of Lee and Dall [4] who demonstrated that using these children and adolescent count thresholds for the activPAL poorly estimated activity intensity versus the ActiGraph over a 24-h period (i.e., concurrent validity) in adults. Importantly, we implemented a 7-d habitual activity measurement period that is reflective of how the activPAL device is typically used by researchers [1]. With that, the introduced method calculated LPA and MPA values statistically equivalent to the PiezoRxD (Table 3), a measure with established criterion validity [12-14[1–6, 8–20,21]]. Although VPA was underpredicted in free-living conditions using the count-METs VPA threshold (22621 counts per 15s epoch), it was at least detectable.

Quantifying activity based on time in an intensity category (e.g., time spent in MPA) versus specific MET values likely explains the slight differences between the results from the treadmill cross-validation and the free-living conditions. Specifically, minor overestimations (e.g., 4.0 METs vs 3.5 METs) are still within the ranges of MPA (3.0-5.9 METs) or VPA (>6 METs). This may explain why the VM method underestimated time spent in VPA (time spent >6 METs) relative to the PiezoRxD in free-living conditions despite being statistically equivalent versus indirect calorimetry in the laboratory settings (indirect calorimetry: 6.4 METs vs VM: 6.1 METs).

Similar to the curvilinear cadence-METs model ($R^2 = 0.83$) [7], and other linear cadence-METs models ($R^2 = 0.58$) [2] and ($R^2 = 0.50$) [21], the logarithmic count-METs model explained a large amount of variance ($R^2 = 0.76$) using the VM activity counts. Future studies that investigate the data processing methods in equating cadence or counts to METs are strongly encouraged to consider the non-linear relationship between these variables rather than incorrectly assuming a linear relationship. Our study is strengthened by validating the counts-MET model in a separate group of participants in a laboratory setting with highly accurate criterion measures (i.e., indirect calorimetry) and controlled methods, as well as in an unstructured free-living condition that enhances the external validity of our findings.

Although the present study extends the literature from children [9] and adolescent [10] populations to the adult population, our findings likely do not apply to older adults or persons with altered gait patterns who may exhibit different counts-METs relationships (i.e., shorter stride lengths). Our inclusion of multiple treadmill speeds and both controlled laboratory and unstructured free-living conditions provides more robust results for assessing the validity of the activPAL monitor. However, the inclusion of more, higher-intensity conditions (e.g., jogging, running, etc.) in the Development group may improve the detection of VPA in this population. Another noteworthy aspect of our study is the inclusion of a number of statistical tests used to determine validity. Such statistical procedures and reporting align with recent guidelines [18] and the analyses implemented may serve to promote best statistical practices in physical activity monitor validation studies. Despite being validated in the uncontrolled setting, our thresholds are inherently based on treadmill walking and it is likely that these thresholds do not apply to other exercise modes such as cycling or swimming. Given the frequent usage of the activPAL to measure habitual activity, further studies improving the detection of VPA in a number of different populations across a variety of activities are warranted.

In conclusion, the present study presents an analytical approach that takes advantage of the tri-axial accelerometry counts provided by the activPAL to accurately determine intensity-related physical activity in a young adult population.

Conflict of interest

All authors must disclose any financial and personal relationships with other people or organisations that could inappropriately influence (bias) their work. Examples of potential conflicts of interest include employment, consultancies, stock ownership, honoraria, paid expert testimony, patent applications/registrations, and grants or other funding.

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Ethical approval

Ethics approval was granted by the Dalhousie University Health Sciences Research Ethics Board (REB# 2019-4786).

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.medengphy.2021.07.014.

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