A data-driven, meaningful, easy to interpret, standardised accelerometer outcome variable for global surveillance

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Abstract

Objectives: Our aim is to demonstrate how a data-driven accelerometer metric, the acceleration above which a person's most active minutes are accumulated, can a) quantify the prevalence of meeting current physical activity guidelines for global surveillance and b) moving forward, could inform accelerometer-driven physical activity guidelines. Unlike cut-point methods, the metric is population-independent (e.g. age) and potentially comparable across datasets. **Design:** Cross-sectional, secondary data analysis. **Methods:** Analyses were carried out on five datasets using wrist-worn accelerometers: children (N=145), adolescent girls (N=1669), office workers (N=114), pre- (N=1218) and post- (N=1316) menopausal women, and adults with type 2 diabetes (N=475). Open-source software (GGIR) was used to generate the magnitude of acceleration above which a person's most active 60, 30 and 2 minutes are accumulated: $M60_{ACC}$; $M30_{ACC}$ and $M2_{ACC}$, respectively. **Results:** The proportion of participants with $M60_{ACC}$ (children) and $M30_{ACC}$ (adults) values higher than accelerations representative of brisk walking (i.e., moderate-to-vigorous physical activity) ranged from 17-68% in children and 15%-81% in adults, tending to decline with age. The proportion of pre-and post-menopausal women with $M2_{ACC}$ values meeting thresholds for bone health ranged from 6-13%. **Conclusions:** These metrics can be used for global surveillance of physical activity, including assessing prevalence of meeting current physical activity guidelines. As accelerometer and corresponding health data accumulate it will be possible to interpret the metrics relative to age- and sex- specific norms and derive evidence-based physical activity guidelines directly from accelerometer data for use in future global surveillance. This is where the potential advantages of these metrics lie.

Keywords: physical activity; population; acceleration; measurement; research-grade accelerometer; wrist-worn

Practical implications

- The magnitude of acceleration above which a person's most active minutes are accumulated throughout the day could be useful for monitoring and surveillance, e.g. prevalence of meeting physical activity guidelines
- Unlike cut-point methods, the metrics are population-independent (e.g. age), do not rely on calibration studies, and no person scores zero
- The metrics can be translated post-hoc in terms of walking/running, providing a public health friendly interpretation of the results relevant to a range of clinical populations
- These metrics will encourage use of accelerometer data for global surveillance of meeting activity guidelines. Further, as accelerometer and corresponding health data accumulate it will be possible to use the metrics to derive evidence-based physical activity guidelines directly from accelerometer data that express recommendations in terms of representative activity type, e.g. 'brisk walking'.

Introduction

National and/or large-scale surveys of physical activity through accelerometers are now commonplace in many countries worldwide[1-5]. The World Health Organisation's recent Global Activity Action Plan on Physical Activity 2018-2030[6] highlights monitoring and surveillance, using robust and reliable data, as the cornerstone to the implementation and evaluation of national strategies. Accelerometers provide a valid measure of physical activity[7]; however, a lack of consensus on robust and consistent methods to reduce and analyse data to create meaningful and easy to interpret outcome variables, is hampering monitoring and evaluation activities.

For example, epidemiological studies and surveillance studies frequently create variables from accelerometer-assessed moderate-to-vigorous physical activity (MVPA) using intensity cut-points. The problems with using cut-points to quantify activity are well documented[8-11] but, briefly, include: (1) cut-points are protocol-, and population- (e.g. age-group) specific, leading to results that are not comparable across studies[8-10]; (2) two participants with similar levels of activity score very differently if one has activity falling just above the cut-point and one has activity falling just below the cut-point; (3) many participants fail to obtain any activity above cut-points (particularly in the vigorous range), consequently a large number of people simply score zero minutes. Recently, in an examination of how cut-points influence estimates of physical activity, Migueles et al.[11,p1] stated that it was ‘not possible (and probably will never be) to know the prevalence of meeting the physical activity guidelines based on accelerometer data’. Clearly a new approach to analysing and interpreting accelerometer data is needed.

An alternative approach is to identify the minimum acceleration value above which a person’s most active minutes, for example 30 mins ($M30_{ACC}$), is accumulated. The active minutes can be accumulated in any way across the day, with no need for the activity to be in bouts, in line with recent physical activity recommendations[12]. With this approach the metric is population-independent and derived from directly measured acceleration, thus not relying on assumptions as cut-points do[9], and the intensity is captured regardless of level of activity with no person scoring zero. This bears similarities to the peak 30 min walking cadence (steps/min) proposed by Tudor-Locke and colleagues[13] as a practical estimate of ‘best natural effort’ during habitual physical activity.

Moving forward, as accelerometer and corresponding health data accumulate, these data-driven population-independent metrics could be used to inform accelerometer-driven physical activity guidelines as recommended by Troiano et al.[10], rather than inappropriately evaluating physical activity assessed by accelerometer cut-points to guidelines developed from self-report data, which are conceptually different[10]. For example, the $M30_{ACC}$ and/or $M60_{ACC}$ that is positively associated with a given health marker, e.g. adiposity, could be determined. This $M30_{ACC}$ and/or $M60_{ACC}$ value could then be used for surveillance which, importantly, would facilitate surveillance using the same physical activity metric as used to garner the evidence. As with the peak cadence[13], the metric itself is population independent, but norms will vary, e.g. by age and sex. As data accumulate, it would be possible to interpret the $M30_{ACC}$ and $M60_{ACC}$ relative to age- and sex- specific norms and/or relative to values associated with health markers.

To facilitate public-health recommendations, translation of the metrics to public-health friendly representative activity types is desirable, e.g. brisk walking, and/or MVPA. This translation is necessarily population-specific and thus bears similarities to cut-point analyses. However, crucially this is only in the translation of the data for activity recommendations because all analyses are carried out on the population-independent metrics[9]. In contrast, when using cut-points, thresholds are imposed on the data from the outset to collapse data into categories for analysis, rendering it impossible to subsequently compare any datasets deploying different cut-points.

For example, assume that a child has an $M60_{ACC}$ value of 225 m*g*. Currently, we do not have the data to compare this to accelerometer-driven physical activity guidelines; however, we can assess whether the child is meeting the current 60 min daily MVPA guideline[12] by comparing their $M60_{ACC}$ value to one of the MVPA cut-points available. According to the 200 m*g* MVPA cut-point published by Hildebrand et al.[14], the child exceeds the 60 minutes of MVPA per day recommendations[12], while according to a more stringent 250 m*g* MVPA cut-point published by Phillips et al.[15], the child does not quite reach the recommendations. If a cut-point approach had been used to analyse the data, the child's score could not be compared to any alternative cut-point or threshold.

For the purposes of a simple demonstration of how these metrics could be used for surveillance of adherence to current physical activity guidelines[12], we looked at the daily average acceleration above which the most active 30 mins ($M30_{ACC}$, adults) or 60 mins ($M60_{ACC}$, children) was obtained. It would be possible to alter the number of minutes over which the minimum acceleration is considered, depending on the health outcome of interest or the guideline being assessed. For example, in a large cross-sectional observational study, Stiles et al.[16] demonstrated that accumulating 1-2 minutes of accelerometer-assessed high intensity activity, equivalent to running, was associated with bone health in pre- and post-menopausal women.

The primary aim of this paper is to demonstrate how the acceleration above which a person's most active minutes are accumulated, can be used to quantify prevalence of meeting existing physical activity guidelines. A secondary aim is to illustrate that, as accelerometer and corresponding health data accumulate, there is potential for these population-independent metrics to be used to inform accelerometer-driven physical activity guidelines.

Methods

Secondary data analyses were carried out on five diverse datasets: 10 y old children[17], adolescent girls[18,19], adult office workers[20], pre- and post-menopausal women[16], and adults with type 2 diabetes[21]. All participants gave assent (children and adolescent girls) or informed consent (adults). Parents/guardians of the children gave written informed consent and parents/guardians of the adolescent girls returned an opt-out consent form if they did not want their child to participate. All studies received the appropriate institutional ethics approval.

In all samples, wrist worn accelerometers were worn 24 h a day for up to 7 days. The children and adult office workers wore the ActiGraph GT9X Link (ActiGraph, Pensacola, FL, USA), the adolescent girls and the adults with type 2 diabetes wore the GENEActiv (ActivInsights Ltd, Cambridgeshire, UK) and the pre- and post-menopausal women wore the Axivity AX3 (Axivity, Newcastle, UK). The pre- and post-menopausal women wore the monitor on their dominant wrist, all other samples wore monitors on the non-dominant wrist. All monitors were initialised to record accelerations at 100 Hz, except the adult office workers whose monitors were initialised at 30 Hz.

ActiGraphs were initialised and downloaded using ActiLife version 6.11.9 (ActiGraph, Pensacola, FL, USA). Data were saved in raw format as GT3X files, before being converted to raw csv file format for signal processing. GENEActivs were initialised and data downloaded in binary format using GENEActiv PC (version 3.1). Axivity data were downloaded from UK Biobank in .cwa format, auto-calibrated, resampled (100 Hz) and converted to .wav format using open-source software (Omgui Version 1.0.0.28; Open Movement, Newcastle, UK).

All accelerometer files were processed and analysed with R-package GGIR version 1.6-7 (http://cran.r-project.org)[22,23]. Signal processing in GGIR included auto-calibration using local gravity as a reference[22] (apart from the Axivity files which were auto-calibrated when converted to .wav files); detection of sustained abnormally high values; detection of non-wear; and calculation of the average magnitude of dynamic acceleration corrected for gravity (Euclidean Norm minus 1 g, ENMO). These were averaged over 1 or 5 s epochs (1s: pre- and post-menopausal women (UK Biobank), 5 s: children, adolescent girls, adult office workers and adults with type 2 diabetes) and expressed in milli-gravitational units (m*g*). Note that as the average over an epoch is used the values are independent of epoch duration.

Participants were excluded if their accelerometer files showed: post-calibration error greater than 0.01 *g* (10 m*g*), fewer than three days of valid wear (defined as >16 h per day), or wear data wasn't present for each 15 min period of the 24 h cycle, i.e. data from at least one day of measurement had to be present for each 15 min period. The following metrics were generated and averaged across all valid days: average acceleration; intensity gradient (intensity distribution[21]); acceleration above which a person's most active X minutes (MX_{ACC}) are accumulated: $M60_{ACC}$ (m*g*); $M30_{ACC}$ (m*g*), $M2_{ACC}$ (m*g*), (within the GGIR package, these metrics are obtained in part2 using: qlevels (0,24 hours): 1380/1440, 1410/1440 and 1438/1440). These MX_{ACC} statistics rank the acceleration for each epoch during the day in descending order to obtain the acceleration above which the person's most active X minutes are accumulated. Note this differs from the peak cadence described by Tudor-Locke et al.[13], which is the average of the cadence for the peak 30 minutes. As acceleration measured at the dominant wrist is approximately 10% higher than the non-dominant[24], magnitudes of $M60_{ACC}$, $M30_{ACC}$ and $M2_{ACC}$ were reduced by 10% for dominant wrist placement (pre- and post-menopausal women).

Analyses: Descriptive statistics were calculated using mean (standard deviation (SD)) for continuous variables and percentage for categorical variables.

Percentiles (5^{th} - 95^{th} percentile) were graphed for females (all samples) and males (where available) for the $M60_{ACC}$, $M30_{ACC}$ and $M2_{ACC}$. Presenting percentiles for each metric illustrates the magnitude of the most active X minutes, from the least to the most active participants, within each sample. To address our primary aim, the proportion of each sample meeting the MVPA physical activity guidelines, operationalised for the purposes of this demonstration as a daily average of 30 min for adults and 60 mins for children and adolescents, was calculated. For MVPA, we estimated acceleration values representative of a brisk walk (5 km/h, ≅ 3.6 METs: 170 m*g* adults; 200 m*g* children[14]) and of a fast walk (5.6 km/h, ≅ 4.5 METs: 250 m*g* adults; 300 m*g* children[14,25,26]). To do this we took the MET values associated with the walking speeds from activity energy expenditure compendiums for adults[25] and children[26], converted these to VO_2 (assuming 1 MET = 3.5 ml/kg/min for adults[25] and 1 MET = 5 ml/kg/min for children[26]), then used the child and adult regression equations presented by Hildebrand et al[14] to obtain estimates of acceleration values representative of brisk and fast walking. In addition, the proportion of pre- and post-menopausal women meeting the recently proposed accelerometer-driven guide of 2 min high-intensity activity associated with bone health[16] was calculated. The thresholds (>1000 m*g* (medium run) pre-menopausal, > 750 m*g*, post-menopausal (slow run)) were generated using dominant wrist data[16], so are adjusted by -10%[24].

Results

Valid accelerometer data files were available for 64% of 10 y old children (N = 145, age (mean (SD)) = 9.6(0.3) y, 57% female), 96% of adolescent girls (age 11-12 y: N = 974, age 12.3(0.4) y; age 13-14y, age 13.6(0.4) y, 100% female), 78% of adult office workers (N = 114, age 41.2(10.9) y, 80% female) and 99% of adults with type 2 diabetes (N = 475, age 64.2(8.7) y, 36% female). All accelerometer files for the pre- and post-menopausal women from UK Biobank meeting the criteria of Stiles et al.[16] were included (N = 1218 pre-menopausal, age 46.2(3.9) y, N = 1316 post-menopausal, age 59.0(5.1) y). Further descriptive characteristics are presented in Supplementary Material. As expected, physical activity volume (average acceleration) tended to decrease and the intensity distribution (intensity gradient) worsen with increasing sample mean age, see Supplementary Material.

Figures 1 and 2 show percentile plots for $M60_{ACC}$, $M30_{ACC}$ and $M2_{ACC}$ for females and males, respectively, in order of increasing sample mean age. Stick figures mark accelerations associated with a brisk walk (5 km/h), fast walk (5.6 km/h) and slow run ($\geq$8 km/h) on the y-axes to illustrate how the data could be translated in a public-health friendly way[14]. The expected age-related decline in intensity of physical activity appeared to be relatively greater the fewer minutes considered (i.e. there is a steeper drop from childhood to adulthood for the $M2_{ACC}$ than the $M30_{ACC}$), but also for higher percentiles (i.e. higher intensity; the top percentiles dropped more steeply than the lower percentiles) within a given outcome (Figures 1b-c, 2b-c). Sex differences were most evident in 10 y old children, with the intensity of boys' activity greater than that of girls' (Figures 1a-c compared to 2a-c).

Table 1 shows the proportion of each sample meeting MVPA guidelines operationalised as 60 min per day (children) or 30 min per day (adults) of brisk walking or fast walking. The MX_{ACC} above which the most active time is accumulated is shown for those meeting and not meeting the guidelines. The proportions of pre- and post-menopausal women meeting the recent accelerometer-derived guide proposed for bone health (2 minutes >1000 m*g* (medium run) pre-menopausal, >750 m*g* (slow run) post-menopausal)[16] were 6% and 13%, respectively (Figure 1c).

Supplementary material. Descriptive characteristics of the five datasets.

		9-10 y old children	Adolescent girls		Adult office workers	Women: UK Biobank		Adults with type 2 diabetes
		(N=145)	11-12 y (N=974)	13-14 y (N=695)	(N=114)	Pre-menopausal (N=1218)	Post-menopausal (N=1316)	(N = 475)
Sex (%)	Males	42.8	0	0	20.4	0	0	64
	Females	57.2	100	100	79.6	100	100	36
Age (y)		9.6 (0.3)	12.3 (0.4)	13.6 (0.4)	41.2 (10.9)	46.2 (3.9)	59.0 (5.1)	64.2 (8.7)
Body size	Height (cm)	137.5 (5.9)	153.5 (7.7)	159.5 (6.8)	165.9 (7.5)	164.9 (6.0)	163.2 (6.1)	168.6 (11.4)
	Mass (kg)	35.2 (8.2)	45.5 (10.8)	53.6 (12.8)	73.1 (17.3)	65.4 (12.0)	68.1 (11.8)	107.5 (14.5)
	Body mass index (BMI) ($kg.m^{-2}$)	18.5 (3.3)	19.2(3.6)	20.9 (4.3)	26.5 (5.9)	24.9 (4.2)	25.6 (4.4)	31.4 (5.4)
	**zBMI	0.63 (1.19)	0.08 (1.30)	0.34 (1.33)				
Accelerometer	Brand	ActiGraph GT9X	GENEActiv	GENEActiv	ActiGraph GT9X	Axivity	Axivity	GENEActiv
	Wrist	Non-dominant	Non-dominant	Non-dominant	Non-dominant	Dominant	Dominant	Non-dominant
*Physical activity	Average acceleration (m*g*)	45.8 (13.1)	37.8 (9.0)	34.3 (7.9)	26.9 (7.7)	*30.6 (8.5)	*27.1 (7.0)	22.0 (7.3)
	†Intensity gradient	-1.96 (0.14)	-2.19 (0.15)	-2.28 (0.17)	-2.55 (0.22)	-2.66 (0.16)	-2.74 (0.16)	-2.74 (0.20)
	‡$M60_{ACC}$ (m*g*)	216.9 (71.5)	180.4 (42.9)	166.7 (37.7)	129.1 (37.9)	*158.3 (47.7)	*139.1 (34.1)	103.9 (36.3)
	‡$M30_{ACC}$ (m*g*)	363.9 (135.5)	260.6 (75.8)	233.0 (63.80	188.1 (95.6)	*226.4 (85.9)	*191.7(56.2)	136.9 (50.5)
	‡$M2_{ACC}$ (m*g*)	1545.1 (518.8)	954.2 (323.7)	771.9 (301.5)	426.5 (216.2)	*522.2 (228.9)	*503.8 (160.3)	305.0 (115.0)

Values are mean (standard deviation) for continuous variables and % for categorical variables.

* Reduced by 10% as acceleration measured at the dominant wrist is approximately 10% higher than measured at the non-dominant (26).

** zBMI: BMI expressed in z-scores for sex and age according to reference curves for the UK (29).

†Measure of the intensity distribution of the 24 h activity profile, see Rowlands et al. (25). A more negative gradient reflects a steeper drop with little time accumulated at mid-range and higher intensities, while a less negative gradient reflects a shallower drop with more time spread across the intensity range.

‡$M60_{ACC}$, $M30_{ACC}$, $M2_{ACC}$: acceleration above which a person's most active minutes (X min, MX_{ACC}) are accumulated.

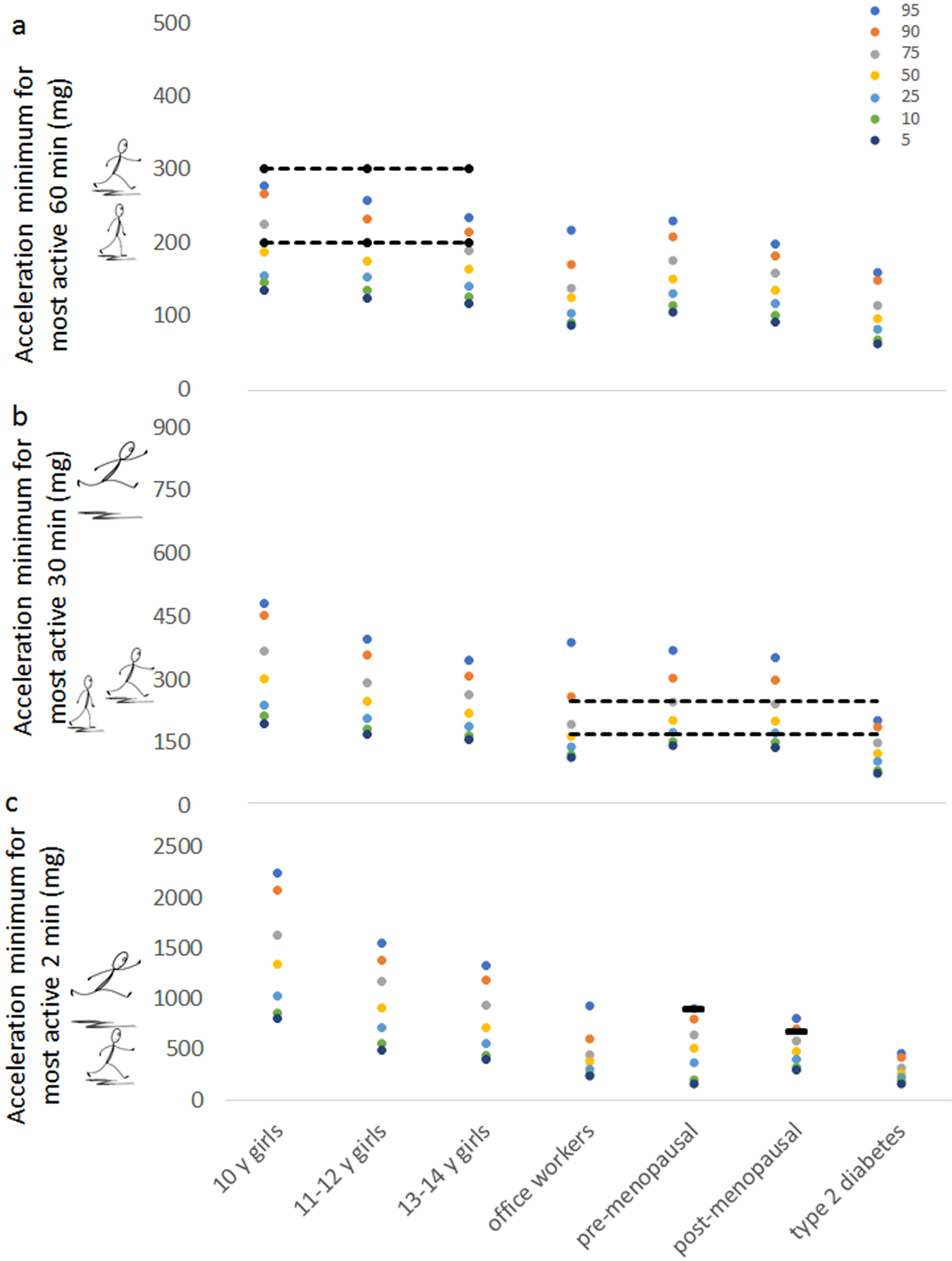

Figure 1: Percentiles for the magnitude of acceleration above which the females' most active (a) 60, (b) 30 and (c) 2 minutes are accumulated: $M60_{ACC}$; $M30_{ACC}$ and $M2_{ACC}$ (m*g*). Black dashes /dashed lines represent: (a) $M60_{ACC}$ and (b) $M30_{ACC}$ at the intensity of a brisk walk (lower dashed line) or fast walk (upper dashed line); (c) $M2_{ACC}$ at the bone health threshold: medium running for pre-menopausal women and slow running for post-menopausal women[16]. The stick figures indicate representative activities associated with the acceleration for: (a) slow walk and brisk walk; (b) slow walk, brisk walk and slow run; c) brisk walk and slow run.

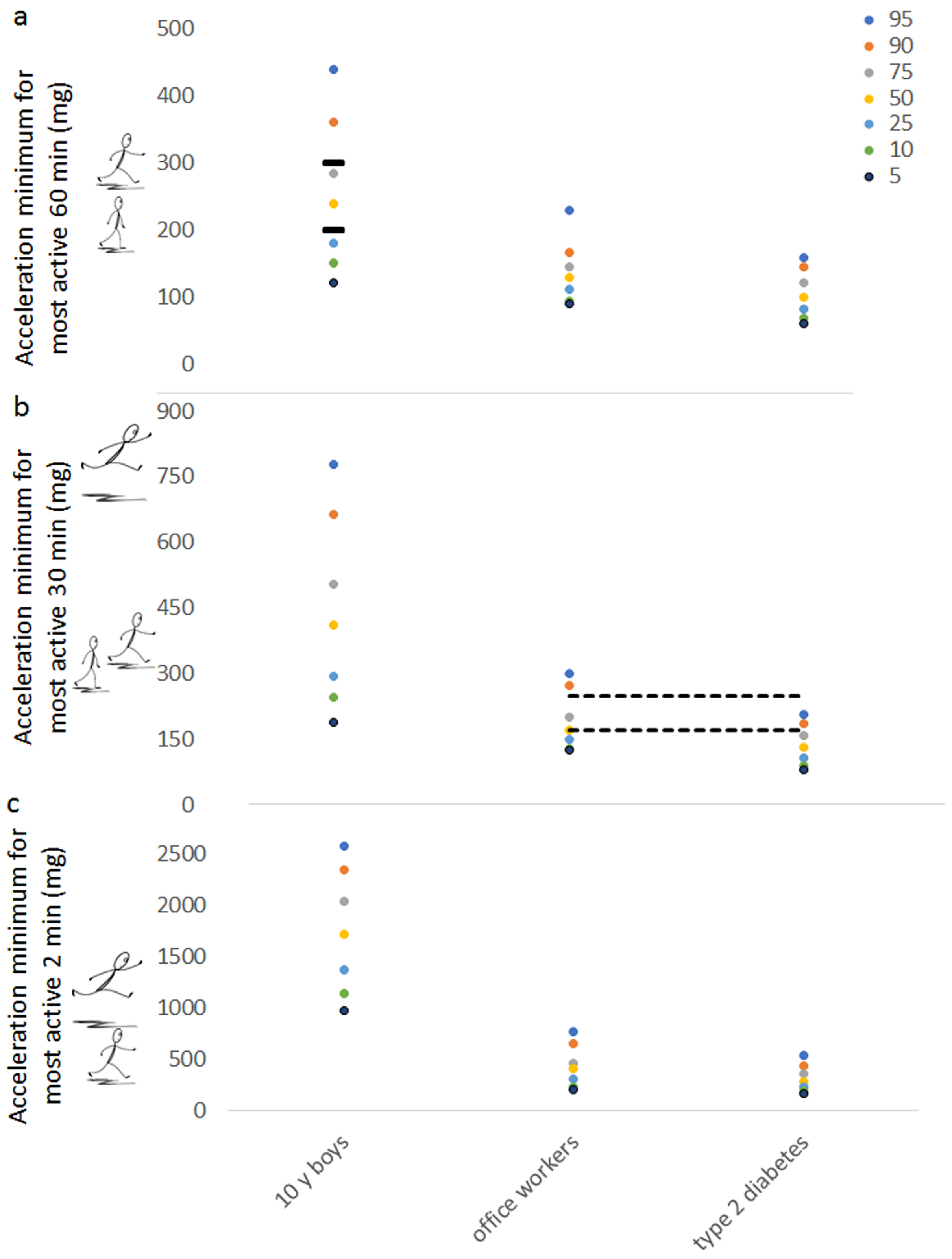

Figure 2: Percentiles for the magnitude of acceleration above which the males' most active (a) 60, (b) 30 and (c) 2 minutes are accumulated: $M60_{ACC}$; $M30_{ACC}$ and $M2_{ACC}$ (m*g*). Black dashes /dashed lines represent: (a) $M60_{ACC}$ and (b) $M30_{ACC}$ at the intensity of a brisk walk (lower dashes / dashed line) or fast walk (upper dashes / dashed line). The stick figures indicate representative activities associated with the acceleration for: (a) slow walk and brisk walk; (b) slow walk, brisk walk and slow run; c) brisk walk and slow run.

Table 1: Proportion of each sample meeting MVPA guidelines operationalised as 60 min per day (children) or 30 min per day (adults) of brisk walking or fast walking

		Brisk walk		Fast walk	
		Female	Male	Female	Male
Children	60 min	>200 m*g*	>200 m*g*	>300 m*g*	>300 m*g*
10 y olds	% meeting guideline	39%	68%	2%	21%
	NO: $M60_{ACC}$	164.9 (21.3)	157.8 (27)	192.0 (42.2)	212.1 (53.1)
	YES: $M60_{ACC}$	242.3 (28.4)	289.1 (74.4)	302.2 (1.64)	377.2 (70.2)
11-12 y olds	% meeting guideline	26%		2%	
	NO: $M60_{ACC}$	161.4 (23.3)		177.6 (36.8)	
	YES: $M60_{ACC}$	235.6 (39.0)		355.2 (43.30	
13-14 y olds	% meeting guideline	17%		1%	
	NO: $M60_{ACC}$	154.6 (25.1)		164.4 (25.6)	
	YES: $M60_{ACC}$	228.1 (30.1)		320.1 (10.5)	
Adults	30 min	>170 m*g*	>170 m*g*	>250 m*g*	>250 m*g*
Office workers	% Meeting guideline	45%	55%	11%	14%
	NO: $M30_{ACC}$	141.7 (18.2)	147.7 (16.0)	161.4 (30.9)	167.5 (27.4)
	YES: $M30_{ACC}$	246.8 (133.6)	212.8 (46.0)	427.9 (188.5)	282.8 (19.5)
Pre-menopausal women	% meeting guideline	81%		25%	
	NO: $M30_{ACC}$	150.8 (15.1)		191.2 (31.3)	
	YES: $M30_{ACC}$	244.5 (86.0)		334.5 (107.6)	
Post-menopausal women	% meeting guideline	63%		11%	
	NO: $M30_{ACC}$	145.6 (17.6)		177.3 (33.5)	
	YES: $M30_{ACC}$	219.0 (53.4)		303.4 (69.9)	
Adults with type 2 diabetes	% meeting guideline	15%	16%	2%	3%
	NO: $M30_{ACC}$	118.7 (23.9)	123.9 (26.5)	129.2 (35.1)	132.8 (33.9)
	YES: $M30_{ACC}$	203.8 (28.4)	221.2 (89.1)	268.8 (15.4)	354.5 (0)

Discussion

Given the rising use of accelerometers, including their use in large-scale surveys[e.g.1-5], it is important to have simple to derive and easy to interpret accelerometer variables that has potential for use to compare physical activity across datasets/populations/countries. This would facilitate global surveillance and the development of evidence-based physical activity guidelines directly from accelerometer data. As data accumulate, physical activity of groups and individuals can be interpreted relative to age- and sex- specific norms and/or relative to values associated with health markers. While the values themselves are not immediately intuitive, this is also true of many metrics that are commonly used by researchers, clinicians and the public[28]. For example, risk thresholds for health markers such as body mass index, blood pressure, and cholesterol are routinely used and widely understood. As outlined by Welk et al.[28], a range of instruments are used to obtain measures of blood pressure, but the use of a standardised metric makes it possible for researchers, clinicians and patients to discuss a common number. This would also be possible with widespread use of standardised population-independent accelerometer measures of physical activity.

In this paper, we demonstrate how presenting percentiles for population-independent metrics such as the $M60_{ACC}$ and $M30_{ACC}$ can be used now to estimate adherence to current MVPA guidelines. The numerous problems associated with applying cut-points to accelerometer data[8-10] are avoided as the data and results presented are data-driven. Comparison to any representative activity, cut-point or, more importantly, any future health-related accelerometer threshold is possible and can be carried out post-hoc with no access to the original data needed. Further, demographic-specific translations can be carried out post-hoc to facilitate public-health friendly recommendations using accelerations representative of typical activities. Crucially, population-specific translation is only for interpretation and has no bearing on analyses or results presented. This means the metrics and results retain their population-independence[9].

Further, comparison or translation is not tied to an exact acceleration value for a representative activity or cut-point. For example, if a child accumulates 60 min of activity in the acceleration range of 185 – 199 m*g*, their $M60_{ACC}$ will be 185 m*g*. Another child may accumulate 60 min with accelerations just exceeding 200 m*g*. With the cut-point method, these similar activity levels look very disparate; zero min of MVPA and 60 min of MVPA, respectively. Their $M60_{ACC}$, on the other hand reflects the smaller discrepancy in activity level that is evident; 185 m*g* and 200 m*g*. At a group level, presenting percentiles for the MX_{ACC} values as illustrated herein (Figures 1 and 2), displays the proportion of a sample achieving X min at any given intensity. In contrast, once cut-points have been applied, any activity accumulated just below a given cut-point will always be disregarded, irrespective of how the data are presented.

By decreasing the number of minutes of interest the metric can be used to focus on aspects of health that benefit from short, high-intensity bursts of activity, e.g. bone health[16, 29]. Accelerometer-derived physical activity intensity guides for bone health have recently been proposed for pre- and post-menopausal women using data from a UK Biobank[16]; these metrics could be used to further test this recommendation and to derive guidelines from accelerometer data specific to bone health in men and children.

To aid translation, we expressed the acceleration magnitudes in relation to representative activities, e.g. brisk walk, fast walk and run. Currently there are limited data from which to draw these estimates. To enhance translation of these metrics there is a need to generate more data showing the acceleration ranges associated with representative activities across a wide range of demographics. Note, this is only for translation and is not necessary for generation of the accelerometer metrics from data, or for developing the evidence base necessary to derive physical activity guidelines directly from accelerometer data.

The acceleration magnitudes tended to be higher for the pre-menopausal women who wore the Axivity on their dominant wrist than for the slightly younger office workers who wore the ActiGraph on their non-dominant wrist. While this may be due to the sedentary nature of the office job, it could reflect the non-representative nature of the samples, indicate that the -10% reduction in acceleration for dominant wrist placement[24] was insufficient, and/or that there were differences between the ActiGraph and the Axivity. While raw data from the GENEActiv and Axivity accelerometers compare well[24], 'raw' data from the ActiGraph GT9X is passed through a filter that suppresses higher intensity accelerations. As the filter suppresses higher accelerations this will be most evident in active populations and for the shorter MX_{ACC} durations and will limit the comparability of data collected with the ActiGraph to data collected with the Axivity or GENEActiv. Further, the accelerometer sampling frequency and epoch differed between some studies. As the metrics are sampling frequency independent this should not impact on the outcomes generated with GGIR, but this needs to be confirmed empirically. It is also possible that the use of 1 s and 5 s epochs may have impacted on the

MX_{ACC} outcomes, however, in our previous study data summarised in 1 s and 5 s epochs were comparable[30]. Crucially, as with any accelerometer outcome, the metrics will differ according to where the monitor is worn, e.g. output collected at the wrist is not comparable to data collected at the hip. Any norms generated for these, or any other, metrics will have to be placement-specific. It is important to consider all of the above when attempting to compare these metrics between studies.

Conclusion

Cut-point approaches to analysing accelerometer data are not appropriate for assessing the prevalence of meeting guidelines globally[11]. Metrics reflecting the acceleration above which the most active minutes are accumulated are a standardised, easy to interpret, and population-independent method that has potential for assessing prevalence of physical activity and comparing activity between demographics and/or studies. These simple to derive variables facilitate global surveillance and dose-response studies. Furthermore, translating the metrics in terms of representative activities (e.g. brisk walking) can provide a public-health friendly interpretation of the results[9]. Currently, guidelines are largely derived from self-report data[10]. As accelerometer and corresponding health data accumulate it will be possible to derive evidence-based physical activity guidelines directly from accelerometer data.

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