Beyond Cut Points: Accelerometer Metrics that Capture the Physical Activity Profile

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ABSTRACT

ROWLANDS, A. V., C. L. EDWARDSON, M. J. DAVIES, K. KHUNTI, D. M. HARRINGTON, and T. YATES. Beyond Cut Points: Accelerometer Metrics that Capture the Physical Activity Profile. Med. Sci. Sports Exerc., Vol. 50, No. 6, pp. 1323–1332, 2018. Purpose: Commonly used physical activity metrics tell us little about the intensity distribution across the activity profile. The purpose of this paper is to introduce a metric, the intensity gradient, which can be used in combination with average acceleration (overall activity level) to fully describe the activity profile. Methods: A total of 1669 adolescent girls (sample 1) and 295 adults with type 2 diabetes (sample 2) wore a GENEActiv accelerometer on their nondominant wrist for up to 7 d. Body mass index and percent body fat were assessed in both samples and physical function (grip strength, Short Physical Performance Battery, and sit-to-stand repetitions) in sample 2. Physical activity metrics were as follows: average acceleration ($Accel_{AV}$); the intensity gradient ($Intensity_{GRAD}$ from the log–log regression line: 25-mg intensity bins [x]/time accumulated in each bin [y]); total moderate-to-vigorous physical activity (MVPA); and bouted MVPA (sample 2 only). Results: Correlations between $Accel_{AV}$ and $Intensity_{GRAD}$ (r = 0.39–0.51) were similar to correlations between $Accel_{AV}$ and bouted MVPA (r = 0.48) and substantially lower than between $Accel_{AV}$ and total MVPA (r Q 0.93). $Intensity_{GRAD}$ was negatively associated with body fatness in sample 1 (P G 0.05) and positively associated with physical function in sample 2 (P G 0.05); associations were independent of $Accel_{AV}$ and potential covariates. By contrast, MVPA was not independently associated with body fatness or physical function. Conclusion: $Accel_{AV}$ and $Intensity_{GRAD}$ provide a complementary description of a person_s activity profile, each explaining unique variance, and independently associated with body fatness and/or physical function. Both metrics are appropriate for reporting as standardized measures and suitable for comparison across studies using raw acceleration accelerometers. Concurrent use will facilitate investigation of the relative importance of intensity and volume of activity for a given outcome. Key Words: INTENSITY GRADIENT, AVERAGE ACCELERATION, GENEACTIV, BODY FATNESS, PHYSICAL FUNCTION

The measurement of physical behaviors with acceler-ometers that can be worn continually and give access to the raw acceleration data is now widespread. Research-grade accelerometers available, and in use in large global surveys, include the GENEActiv, Axivity, and ActiGraph (GT3X+, GT9X/Link) (1–7). Despite the potential to describe the 24-h physical behavior profile, output variables derived from accelerometer data are commonly limited to overall activity level and time spent in specific intensity categories such as moderate-to-vigorous physical activity (MVPA) and/or sedentary time.

Overall activity level, defined as average acceleration over a 24-h period, is directly measured and does not rely on population-specific calibration protocols to derive outcome measures; thus, average acceleration is comparable across studies and populations. However, it tells us little about the intensity distribution; for example, it is possible to have a high average acceleration because of a large volume of light-intensity activity and relatively little or no MVPA, or because of a substantial amount of MVPA with a large volume of sedentary time. It is important to capture both overall activity and intensity distribution because, for some health markers and outcomes, it appears the volume of activity is more important

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than the pattern of intensity (e.g., [8–10]), but for others the converse appears to be true (e.g., [11–13]).

Physical activity intensity information is usually expressed as time spent within cut points that have typically been derived using validation studies. These cut points are heavily depen-dent on the calibration sample and the protocol used to derive the cut points (14,15), leading to problems comparing outcomes across studies and/or populations (15,16). Consequently, the validity of these outcomes depends not only on the validity of the measure of acceleration but also on the validity of the algorithm. A further consideration is average acceleration, time below cut points (e.g., inactive time), and time above cut points (e.g., MVPA), which are typically highly intercorrelated, suggesting relatively little unique information is obtained from the measures (e.g., as seen in data from (11,17,18)).

A metric is needed that captures the intensity distribution, does not rely on calibration protocols (that are, by nature, population and protocol specific), and is more independent of overall activity level and, thus, can be used alongside av-erage acceleration. The two metrics together would use the rich nature of the data available to more fully describe the 24-h physical behavior profile and, critically, would depend only on the validity of accelerometers at measuring acceleration, rather than also being population or protocol specific.

The purpose of this paper was to introduce a novel metric that describes the intensity distribution of the accelerations experienced over a 24-h period and can be used in combination with average acceleration to fully describe the activity profile. To demonstrate the potential of the new metric, we applied both metrics to two very different data sets: adolescent girls and adults with type 2 diabetes. In particular, we 1) investigated whether the intensity gradient was more independent of (i.e., less highly correlated with) average acceleration than MVPA and inactive time, 2) investigated whether independent relationships of overall activity level and the intensity distribution existed with body fatness (adolescent girls and adults with type 2 diabetes) and physical function (adults with type 2 diabetes), and 3) demonstrated how results based on analyses of the directly measured acceleration metrics can be translated to easily interpretable physical activity intensity outcomes post hoc.

METHODS

Sample 1 (Adolescent Girls)

Data were obtained from the baseline time point of the evaluation of the Youth Sports Trust_s Girls Active school-based physical activity program (19). This has been previously described (19), but in brief, 20 schools in and on the boundary of Leicestershire and Rutland (UK) took part with approximately 90 girls, 11–14 yr old, invited to participate at random from each school. Parents returned an opt-out consent form if they did not want their child to participate, and the girls themselves provided verbal assent. Ethical approval for the evaluation was obtained from the University of Leicester_s College of Medicine and Biological Sciences Research Ethics representative, United Kingdom.

In brief, the data were collected in measurement sessions run during the school day. Participating girls were requested to wear a GENEActiv accelerometer on their nondominant wrist (defined as the hand they do not normally write with) 24 hId[j1] for 7 d after the measurement session. Height, sitting height, and body mass were measured using standardized procedures. Body mass index (BMI) was calculated and expressed in z-scores of BMI for age according to reference curves for the United Kingdom (20). Age was calculated from date of birth to date of measurement; ethnicity was self-reported and later collapsed into categories of White European, South Asian, or other; and socioeconomic status (SES) was estimated using the index of multiple deprivation from self-reported postcode. Age at peak height velocity was calculated as an indicator of biological maturity and categorized into ''average maturing,'' ''early maturers,'' or ''late maturers'' (21). Percent body fat was estimated using pediatric bioelectrical im-pedance scales (Tanita SC-330ST; Tanita Europe BV, Middlesex, UK).

Sample 2 (Adults with Type 2 Diabetes)

Data were obtained from adult participants (18–75 yr) enrolled in the ongoing CODEC study (Chronotype of Patients with Type 2 Diabetes and Effect on Glycaemic Control; Clinical Trial Registry Number: NCT02973412). Adults were recruited from both primary and secondary care using direct and opportunistic marketing. Eligible adults were sent an invitation pack containing a patient information leaflet, letter of invitation, and reply slip with prepaid envelope. All participants provided written informed consent. Ethical approval was obtained from the local NHS research ethics committee.

Study data were collected in a single session during the patient_s next outpatient appointment unless the patient requested otherwise. The measures relevant to this study were age (from date of birth to date of measurement), ethnicity (self-reported and later collapsed into categories of White [W], South Asian [SA], or other), sex, body mass, height, BMI, percent body fat from bioelectrical impedance scales (Tanita SC-330ST, Tanita Europe BV), and measures of physical function. With the exception of percent body fat and physical function, the above measures were all part of the usual care routine. Physical function measures included the following:

Handgrip strength (kg): Measured three times in the left and right hand using a digital hand held dynamometer, with the elbow flexed and the forearm in a neutral position. The average of the maximum readings for the left and right hand was taken.

Sit-to-stand 60 test: The number of times a participant could stand from a chair in 60 s was recorded.

Short Physical Performance Battery (SPPB): This consisted of chair stands, standing balance, and gait speed (detailed below). The SPPB score was the sum of the three tests and could range from 0 to 12 points, with a high score

indicating better performance. For details of scoring, see Puthoff (22).

Chair stands: The participant started from a seated position on a hard, upright chair, with the feet flat on the floor and the knees bent at 90-. The time taken for the participant to stand up fully and then return to sitting, without using the hands five times, was measured (0–4 points).

Standing balance: This was tested in three progressive positions. If the participant was able to complete 10 s in the specified position, then the starting position was progressed to the next stage (0–4 points).

Feet together
Semitandem
Tandem

Gait speed: The time taken for the participant to walk 2.44 m (8 ft) on a level course was measured (0–4 points).

At the end of the session, participants were given a GENEActiv accelerometer and asked to wear it on their nondominant wrist (defined as the hand they do not normally write with) 24 hId^{j1} for 7 d. They were provided with a prepaid padded envelope to return the device at the end of the assessment period.

Accelerometer Data Processing

The GENEActivs were initialized to collect data at 100 Hz and uploaded using GENEActiv PC software version 3.1. The GENEActiv.bin files were analyzed with R-package GGIR version 1.2–2 (http://cran.r-project.org) (23,24). Signal processing in GGIR includes autocalibration using local gravity as a reference (24), detection of sustained abnormally high values, detection of nonwear, and calculation of the average magnitude of dynamic acceleration corrected for gravity (Euclidean Norm minus 1g, ENMO) averaged over 5-s epochs and expressed in milligravitational units (mg).

Participants were excluded if their accelerometer files showed postcalibration error greater than 0.01g (10 mg), fewer than 3 d of valid wear (defined as Q16 hId^{j1}; Rowlands et al. (17,18)), or missing wear data for each 15-min period of the 24-h cycle. Detection of nonwear has been described in detail previously (see ''Procedure for nonwear detection'' in supplementary document to van Hees et al. (23)). Briefly, nonwear is estimated based on SD and value range of each axis, calculated for 60-min windows with a 15-min sliding window. The window is classified as nonwear if, for at least two out of the three axes, the SD is less than 13 mg or the value range is less than 50 mg. The default nonwear setting was used; that is, invalid data were imputed by the average at similar time points on different days of the week. Therefore, the outcome variables were based on the complete 24-h cycle (1440 min) for all participants. The distribution of time spent in intensity bins (categories) of 25 mg resolution (0–25, 25–50, 50–75,I 4000, 94000) was calculated.

Physical activity was expressed as average acceleration across the day (ENMO, mg), time accumulated in MVPA per day, and time spent inactive (see below). For each sample, all MVPA outcomes were defined to be consistent with previous research within that population for comparative purposes. For the adolescent girls, $MVPA_{TOTAL}$ was defined as time accumulated above an acceleration of 200 mg (25). For the adults, $MVPA_{TOTAL}$ was defined as time accumulated above an acceleration of 125 mg as presented in a recent paper using data from UK Biobank (26); $MVPA_{BOUTS}$ was defined as time accumulated in 10-min bouts above an acceleration of 100 mg (25), where at least 80% of the bout is above the 100-mg threshold as used in previous research (5,27). Inactive time was defined as time accumulated below 50 mg for both samples (17,28,29).

Metric to Describe Intensity Distribution across the Physical Activity Profile

There is a negative curvilinear relationship between inten-sity and time accumulated at that intensity; i.e., the total time for all participants is 1440 min (24 h), but the vast majority of time is accumulated in the 0- to 25-mg intensity bin, with time accumulated rapidly dropping off as intensity increases and minimal time accumulated at very high intensities, e.g., 91000 mg. The nature of the curvilinear relationship for a given participant provides a good descriptor of their physical activity intensity distribution. To describe this curvilinear re-lationship, for each participant we transformed the curvilinear relationship into a straight-line relationship by taking the natural log of the two wide ranging quantities of intensity and time; that is, the midrange of each of the intensity bins (e.g., 0–25 mg bin = 12.5 mg) and the time accumulated in each intensity bin. We recorded the R^2 (indicative of the goodness of fit of the linear model), gradient, and constant of the linear regression equation for each participant. The gradient was always negative, reflecting the drop in time accumulated as intensity increases; a higher constant and more negative (lower) gradient reflects a steeper drop with little time accumulated at midrange and higher in-tensities (Fig. 1A), whereas a lower constant and less negative (higher) gradient reflects a shallower drop with more time spread across the intensity range (Fig. 1B).

Analyses. Descriptive statistics were calculated for each variable using mean (SD) for continuous variables and percentage for categorical variables. Average acceleration was used as the metric for overall activity, and the gradient of the participant_s log–log linear regression line (intensity gradient) was used as the metric for physical activity distribution.

The two activity metrics were examined and exemplar data plotted to demonstrate how the average acceleration and intensity gradient differed between and within samples. Independent-samples t-tests were used to compare the two activity metrics across samples.

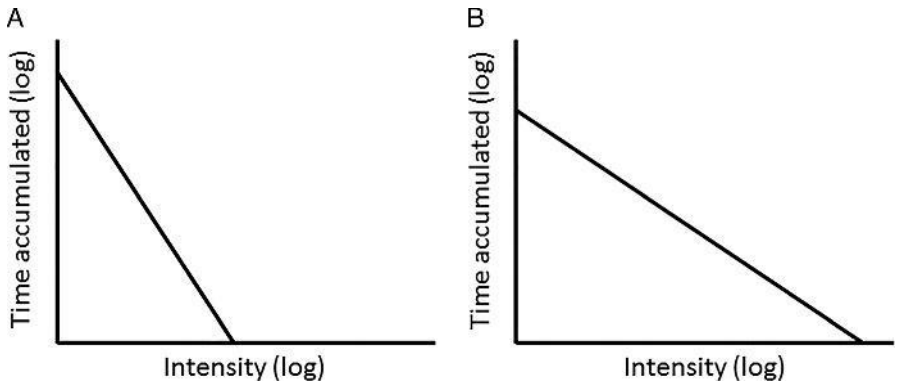

FIGURE 1—A. A steeper, more negative (lower) gradient with a higher constant (y-intercept) showing a steep drop in time accumulated with increasing intensity (left)—a poorer intensity profile. B. A shallower, less negative (higher) gradient with a lower constant (y-intercept) showing more time spread across the intensity range (right)—a better intensity profile.

Intercorrelations of Activity Variables

Pearson_s correlation coefficients were used to investigate the intercorrelations between the various activity output variables within each sample to determine whether the in-tensity gradient was more independent of average accelera-tion than standard intensity metrics.

Associations between the Two Activity Metrics, Body Fatness and Physical Function

Sample 1 (adolescent girls). To control for clustering at the school level, generalized estimating equations were used to determine whether each of the two activity metrics was associated with percent body fat and BMI z-score (dependent variables) (model 1). Model 2 further controlled for potential covariates (age, biological maturity, SES, and ethnicity), and finally model 3 additionally controlled for the alternate activity metric to test whether associations were independent.

Sample 2 (adults with type 2 diabetes). There was no clustering in this data set, so multiple linear regression analyses were used to assess whether each of the activity metrics was associated with the following dependent vari-ables: percent body fat, BMI, grip strength, sit-to-stand test score, and SPPB score (model 1). Model 2 was adjusted for potential covariates (age, sex, SES, ethnicity, and percent body fat [physical function variables only]), and model 3 additionally for the alternate activity metric to test whether associations were independent.

Analyses were repeated replacing the intensity gradient with $MVPA_{TOTAL}$ (both samples) and $MVPA_{BOUTS}$ (sample 2 only). This allowed comparison of results from our new metric, the intensity gradient, to those seen with MVPA metrics.

Continuous variables were centered before entry into generalized estimating equations and regression analyses. The variance inflation factor (VIF) was calculated to check for multicollinearity; a value 95 was taken to indicate if the effects of the predictors could not be reliably estimated (30).

Translation of Results

Increases in a participant_s average acceleration can be made by adding varying durations of physical activity at any intensity greater than the average acceleration. The intensity of the physical activity added will have an effect on the intensity gradient, as it will change the distribution of time across the intensity bins. Whether overall activity, the pattern of activity of both are important for a given health outcome will determine whether an intervention should target the av-erage acceleration (for overall activity), the intensity gradient (for the pattern of activity), or both.

To demonstrate how adding physical activity may affect average acceleration and intensity gradient, we determined the time spent in specific activities that would need to be accumulated to increase the overall activity level of partici-pants from samples 1 and 2 by 1 SD. Next, we explored the effect on the intensity gradient of each option. We assumed that the introduced activity would replace time spent at the average acceleration. Therefore, for a given activity, the time required is calculated as follows: 1440 (increase in average acceleration required by activity at that intensity)/(acceleration associated with that activity j average acceleration). We also show how the recommended activities for a given increase in activity level can be tailored toward a particular balance of in-tensities. This may be desirable because of the intensity distri-bution being important for a given health outcome, or to take into account the preferences of a given demographic/individual participant when prescribing or recommending activity.

The representative activities we used to translate the findings from the accelerometer metrics were as follows: pottering/slow walking (approximately 3 $kmIh^{j1}$), brisk walking (approximately 5 $kmIh^{j1}$), fast walking (approximately 6.5 $kmIh^{j1}$, adults only), slow running (approximately 8 $kmIh^{j1}$), and medium running (approximately 10 $kmIh^{j1}$). The acceleration values indicative of these activities and used to calculate the time estimates were taken from Hildebrand et al. (25), Phillips et al. (31), and Esliger et al. (32). For the adolescents, 100 mg was used for pottering/light walking, 200 mg for brisk walking, 800 mg for slow running, and 1000 mg for medium running. For the

TABLE 1. Descriptive characteristics of sample 1 and sample 2.

	Sample 1 (N = 1669), Adolescent Girls	Sample 2 (N = 295), Adults with Type 2 Diabetes
Sex		
Male	0	60.3
Female	100	39.7
Age (yr)	12.8(0.8)	63.2(9.7)
SES[a]	5.5(2.9)	6.3(3.0)
Body size		
Height (cm)	155.9(8.0)	168.1(10.0)
Mass (kg)	48.8(12.4)	89.7(17.6)
BMI (kgImi[2])	19.9(4.0)	31.6(5.3)
BMI z-score	0.19(1.33)	–
Percent body fat	24.1(7.7)	35.0(8.5)
Biological maturity		
Age at peak height velocity	12.1(0.5)	–
Early maturer	16.0	–
On time	68.2	–
Late maturer	15.8	–
Ethnicity		
White[b]	77.3	77.6
South Asian	11.2	17.2
Other	11.5	5.2
Physical function		
Grip strength (kg)	–	28.5(10.1)
Sit-to-stand 60	–	22.1(7.8)
SPPB	–	9.9(2.0)
Physical activity[e]		
Average acceleration (mg)	36.3(8.7)	22.1(7.5)
$MVPA_{TOTAL}$ [c]	45.5(20.4)	42.2(32.8)
$MVPA_{BOUTS}$ [d]	–	9.3(20.4)
Inactive time (G50 mg)	1163.5(53.9)	1240.3(78.3)
Intensity regression line[e]		
Intensity gradient	j2.47(0.18)	j3.11(0.26)
Constant	14.7(0.89)	16.8(1.0)
Variance explained (R^2, %)	95.0(1.8)	92.7(3.3)

Values are presented as mean (SD) for continuous variables and % for categorical variables. [a]SES is measured by the index of multiple deprivation 2015 decile score, which ranges from 1 to 10, where 1 is the least deprived and 10 is the most deprived.
[b]White European for sample 1 and White for sample 2.
[c]$MVPA_{TOTAL}$: total accumulated MVPA for adolescent girls (9200 mg) and adults with type 2 diabetes (9125 mg).
[d]$MVPA_{BOUTS}$ accumulated in 10-min bouts for adults with type 2 diabetes (9100 mg).
[e]All physical activity/intensity regression line metrics different between groups (P G 0.001).

adults, 80 mg was used for pottering/light walking, 175 mg for brisk walking, 400 mg for fast walking, 750 mg for slow running, and 1000 mg for medium running.

RESULTS

The descriptive characteristics are presented in Table 1. GENEActiv files were available for 1730 participants in sample 1 and 296 participants in sample 2. Excluded participants totaled 61 for sample 1 (6 failed calibration, 24 incomplete 24-h cycle, and 31 fewer than three valid days) and 1 for sample 2 (incomplete 24-h cycle), resulting in a final accelerometer sample size of 1669 for sample 1 and 295 for sample 2. All comparable activity measures differed significantly between the two groups, with the adolescent girls (sample 1) having higher average acceleration and intensity gradient and lower inactive time and regression line constant (intercept). The log–log regression line showed strong linear relationships in both samples (R^2 9 0.92, P G 0.001) but was significantly higher in the adolescent girls (sample 1).

Figure 2 shows the log–log intensity regression line for a representative participant from each sample. The representative participant from sample 1 (solid circles) has an average acceleration level and intensity gradient that equate to the mean value for each for the sample. Correspondingly, the representative participant from sample 2 (open triangles) has an average acceleration level and intensity gradient that equate to the mean for each for sample 2. The less active profile of the adult with type 2 diabetes (sample 2, open triangles) can clearly be seen: steeper gradi-ent, lower accumulated accelerations across all but the lowest intensity bin, and the lack of accelerations at the higher in-tensities. These characteristics are captured by the combina-tion of the two physical activity metrics: acceleration average and intensity gradient.

To demonstrate how the intensity gradient can differ, when the average acceleration does not, a log–log plot for two participants with equally high average acceleration (approximately 2 SD above their sample means) is shown in Figure 3A for sample 1 (top left) and Figure 3B for sample 2 (top right). One of the participants in each plot has a steep intensity gradient (approximately 2 SD below their sample mean) and one has a shallow intensity gradient (approximately 2 SD above their sample mean). The same plots for two participants with equally low average acceleration (approximately 2 SD below their sample mean) are shown in Figures 3C for sample 1 (bottom left) and Figure 3D for sample 2 (bottom right). The participants with steeper gradients accumulate more time in low-to-mid range intensities, whereas the participants with the shallower gradients accumulate more time at relatively high intensities. This results in equivalent average acceleration values within sample.

Intercorrelations of Activity Variables

Average acceleration was strongly positively associated with $MVPA_{TOTAL}$ in both samples (r Q 0.93, P G 0.001), moderately associated with $MVPA_{BOUTS}$ in adults with type 2 diabetes (r = 0.48, P G 0.001), and strongly negatively associ-ated with inactive time in both samples (r e j0.88, P G 0.001). Correlations between average acceleration and the intensity gra-dient were still significant, but considerably weaker (sample 1:

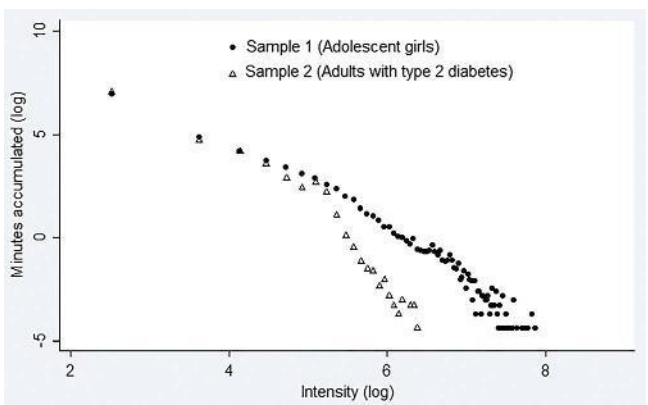

FIGURE 2—Log–log Intensity regression line for representative participants from sample 1 (solid circles) and sample 2 (open triangles). Both participants have the mean average acceleration and mean intensity gradient for their sample.

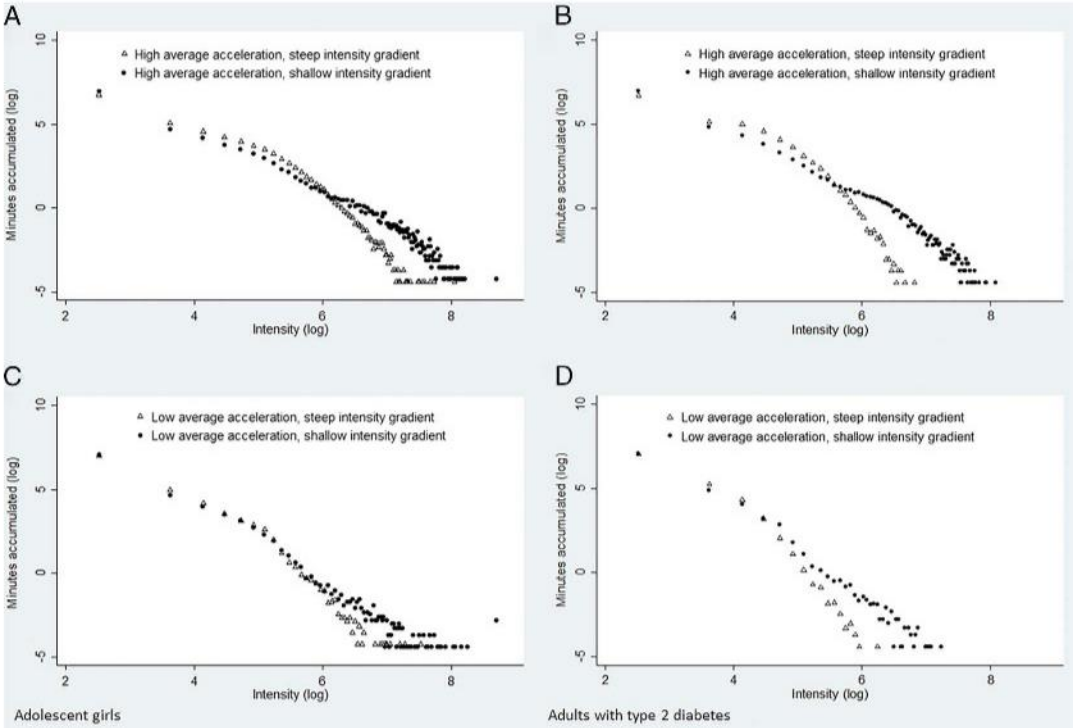

FIGURE 3—Intensity regression line for representative participants with high average acceleration and steep (open triangle) or shallow (solid circle) intensity gradients from sample 1 (A) and sample 2 (B); low average acceleration and steep (open triangle) or shallow (solid circle) intensity gradients from sample 1 (C) and sample 2 (D). Note that average acceleration is similar within each plot. Steep and shallow gradients are similar within each sample (vertically aligned plots).

r = 0.39; sample 2: r = 0.51; both P G 0.001), than for average acceleration with $MVPA_{TOTAL}$ or inactive time, demonstrating the metrics were more independent. Similarly, correlations between the intensity gradient and $MVPA_{TOTAL}$ (sample 1: r = 0.34; sample 2: r = 0.51; both P G 0.001), $MVPA_{BOUTS}$ (r = 0.29, P G 0.001), and inactive time were all considerably weaker (r e j0.39 P G 0.001) than the corresponding correlations with average acceleration. All intercorrelations between activity metrics are shown in Table, Supplemental Digital Content 1, Intercorrelations between activity metrics for samples 1 and 2, http://links.lww.com/MSS/B202.

Associations between the Two Activity Metrics, Body Fatness and Physical Function

Table 2 presents the results of the regression models considering associations of the two physical activity metrics with body fatness (percent body fat and BMI z-score/BMI) in both samples (upper part of Table) and with physical function in sample 2 (lower part of Table). Corresponding results for MVPA are shown in Table, Supplemental Digital Content 2, Associations of average acceleration and MVPA with body fatness (samples 1 and 2) and physical function (sample 2), http://links.lww.com/MSS/B203.

Average Acceleration and the Intensity Gradient (Table 2)

Sample 1 (adolescent girls). Average acceleration was negatively associated with percent body fat, but not BMI z-score, in the unadjusted model (model 1, Table 2). The association did not persist after adjusting for covariates (models 2 and 3). The intensity gradient was negatively associated with both percent body fat and BMI z-score, with both associations remaining significant after adjusting for covariates and independent of average acceleration (models 2 and 3). The VIF was e1.3 in all cases. An increase of one unit in the intensity gradient was associated with a per-cent body fat 6.03 percentage points lower and BMI z-score 0.81 U lower. As the size of the 95% confidence interval (CI) for the intensity gradient was approximately 0.35, the difference in percent body fat and BMI z-score associated with an intensity gradient at the lower and upper limits of the 95% CI was approximately 2 percentage points and 0.28 U, respectively.

Sample 2 (adults with type 2 diabetes). Average acceleration was negatively associated with both percent body fat and BMI (model 1, Table 2). These associations persisted after adjusting for covariates and were independent of intensity gradient (models 2 and 3). The intensity gradient was significantly negatively associated with percent body fat and BMI in the unadjusted model (model 1) but only with BMI after adjusting for covariates (model 2), and not inde-pendent of average acceleration for either percent body fat or BMI (model 3). The VIF was e1.4 in all cases. The difference in percent body fat and BMI associated with average acceleration at the lower and upper limits of the 95% CI was approximately 2 percentage points and 2 $kgIm^{j2}$, respectively.

TABLE 2. Associations of the two physical activity metrics with percent body fat (samples 1 and 2) and physical function (sample 2).

	Model 1		Model 2		Model 3		Independent Effect[a]
	Coefficient	95% CI	Coefficient	95% CI	Coefficient	95% CI	(Model 3)
Sample 1 (adolescent girls)	Pairwise N = 1527–1638		Listwise N = 1521		Listwise N = 1521		
Generalized estimating equations							
Percent body fat							
Average acceleration (mg)	j0.09	j0.13, j0.05	j0.01	j0.05, 0.02	0.03	j0.01, 0.07	X
Intensity gradient[b]	j9.15	j11.46, j6.83	j5.58	j7.36, j3.81	j6.03	j7.96, j4.09	(
BMI z-score							
Average acceleration (mg)	j0.01	j0.01, 0.00	0.01	j0.00, 0.01	0.01	0.00, 0.02	(
Intensity gradient[b]	j1.17	j1.53, j0.81	j0.66	j0.88, j0.44	j0.81	j1.04, j0.58	(
Sample 2 (adults with type 2 diabetes)	Pairwise N = 260–291		Listwise N = 253–279		Listwise N = 253–279		
Multiple regression							
Percent body fat							
Average acceleration (mg)	j0.13	j0.26, j0.00	j0.15	j0.26, j0.05	j0.14	j0.24, j0.03	(
Intensity gradient[b]	j7.25	j10.82, j3.68	j3.09	j6.34, 0.15	j1.27	j4.55, 2.22	X
BMI (kgIm^{j2})							
Average acceleration (mg)	j0.13	j0.21, j0.05	j0.15	j0.23, j0.08	j0.14	j0.22, j0.05	(
Intensity gradient[b]	j2.88	j5.03, j0.73	j2.70	j5.09, j0.31	j0.61	j3.37, 1.78	X
Average grip strength (kg)							
Average acceleration (mg)	0.12	j0.03, 0.28	0.09	j0.04, 0.23	0.03	j0.11, 0.17	X
Intensity gradient[b]	11.09	6.63, 15.56	4.44	0.60, 8.27	4.05	0.04, 8.06	(
Sit-to-stand 60 (repetitions)							
Average acceleration (mg)	0.25	0.11, 0.40	0.22	0.06, 0.38	0.13	j0.05, 0.30	X
Intensity gradient[b]	8.83	5.83, 11.83	7.74	4.36, 11.13	6.03	2.04, 10.02	(
SPPB							
Average acceleration (mg)	0.06	0.03, 0.09	0.04	0.01, 0.07	0.02	j0.02, 0.05	X
Intensity gradient[b]	2.19	1.44, 2.94	1.76	1.05, 2.47	1.55	0.67, 2.44	(

Model 1 adjusted for clustering at school level only (sample 1) or unadjusted (sample 2). Model 2 adjusted for potential covariates. Model 3 further adjusted for alternate activity metric. Significant associations are denoted in bold.

[a]The final column indicates whether the associations with each activity metric were independent of the other metric (from model 3).

[b]Intensity gradient: gradient of the regression line from log–log plot of intensity (x) and minutes accumulated (y).

Average acceleration was not associated with grip strength but was positively associated with sit-to-stand 60 and SPPB (model 1, Table 2). These associations remained after adjusting for covariates (model 2) but were not independent of intensity gradient (model 3). The intensity gradient was positively as-sociated with grip strength, sit-to-stand 60, and SPPB score (model 1), with all associations remaining significant after adjusting for covariates (model 2) and independent of average acceleration (model 3). The VIF was e2.1 in all cases. The size of the effect associated with activity levels at the upper and lower ends of the 95% CI for each of the scores was approximately 2.6 kg for grip strength, three extra sit-to-stand 60 reps, and an SPPB score 0.8 higher (just under half a SD).

Average Acceleration and MVPA (SDC2)

Sample 1 (adolescent girls). $MVPA_{TOTAL}$ was negatively associated with percent body fat when adjusted for clustering at the school level only, but not after adjusting for covariates. It was not possible to test for independent effects of MVPA and average acceleration because of multicollinearity (VIF, 10.4–10.5).

Sample 2 (adults with type 2 diabetes). $MVPA_{TOTAL}$ was negatively associated with percent body fat and BMI and positively associated with sit-to-stand 60 and SPPB; these associations persisted after adjusting for covariates. It was not possible to test for independent ef-fects of $MVPA_{TOTAL}$ and average acceleration because of multicollinearity (VIF, 7.7–8.1).

$MVPA_{BOUTS}$ was negatively associated with percent body fat and BMI and positively associated with sit-to-stand 60 and SPPB, but only the association with BMI remained after adjusting for covariates. No independent effects of $MVPA_{BOUTS}$ were evident. The VIF was e2.1 in all cases.

Translation of Results

An increase in the average acceleration level of 1 SD (an increase of 8.7 and 7.5 mg for samples 1 and 2, respectively) could be achieved by replacing time per day spent at the average acceleration level with:

Sample 1:

1. approximately 3 h of pottering around/slow walking,
2. approximately 75 min of brisk walking,
3. approximately 16–17 min of slow running, or
4. approximately 13 min of medium running.

Sample 2:

1. approximately 3 h of pottering around/slow walking,
2. approximately 65–70 min of brisk walking,
3. approximately 30 min of fast walking,
4. approximately 15 min of slow running, or
5. approximately 11 min of medium running.

The increase in average acceleration to be obtained from each intensity/activity can be manipulated as long as the sum of the increases is equal to the overall average acceleration increase needed (8.7 and 7.5 mg for samples 1 and 2, respec-tively, in the examples). Thus, a combination of activities in a given day can be used to gain the same increase in average acceleration. For example, in sample 2:

6. 1 h of slow walking (2.7 mg) and 30 min of brisk walking (3.2 mg) and 6 min of fast walking (1.6 mg), total = 2.7 + 3.2 + 1.6 = 7.5 mg.

Alternatively, if higher-intensity activity was to be emphasized, the same increase in average acceleration could be obtained from

7. 25 min of slow walking (1.1 mg) and 25 min of brisk walking (2.8 mg) and 7–8 min of slow running (3.6 mg), total = 1.1 + 2.8 + 3.6 = 7.5 mg.

All options would increase the average acceleration by the SD of the sample, but the options would have differing effects on the intensity gradient (note, the effect on the intensity gradient will also depend on the participant_s initial activity profile). The effect of each of these on the intensity gradient for a participant from sample 2 (adults with type 2 diabetes) with a low average acceleration and a low intensity gradient (1 SD below the sample mean for each) is depicted in Figure 4. The order of the options reflects the effect on the intensity gradient, with more negative/null effects at the bottom and the most positive effect at the top (exact values for the change in the intensity gradient for our representative participant are in a column in the middle of the plot). The length of the bars represents the total activity time, and the patterning of the bars represents the combination of activity types included in the option; the more dense the patterning, the more intense the activity. The two lowest-intensity options may have a detrimental effect on the intensity gradient (make it steeper), and the more intense the activities selected, the more positive the effect on the intensity gradient (makes it shallower). The same pat-tern is true for sample 1 (adolescent girls, not shown), but when adding higher-intensity activities (slow running or medium running), the effects on the intensity gradient were more pronounced in adults with type 2 diabetes.

DISCUSSION

We have proposed a novel new metric, the intensity gradi-ent, which describes the intensity distribution of the physical activity profile. It is relatively independent of overall activity, in comparison with the intensity variables currently deployed; for example, MVPA and inactive time. In conjunction with average acceleration (a measure of overall activity level), the two metrics provide a detailed picture of an individual_s physical activity profile. Both metrics are calculated from the directly measured acceleration, minimizing the error associated with using physical behavior outcomes that are further removed from the measured variable (33). Neither relies on calibration protocols, and therefore both are protocol and population independent, facilitating comparisons between studies and populations (33).

We have demonstrated the added value of using the in-tensity gradient to describe the physical activity profile by investigating relations with body fatness and physical func-tion. The intensity gradient was negatively associated with body fatness in adolescent girls and positively associated with physical function in adults with type 2 diabetes; these associations were independent of overall activity level, as assessed by average acceleration. By contrast, $MVPA_{TOTAL}$ was highly correlated with average acceleration, and $MVPA_{BOUTS}$ was not independently associated with body fatness or physical function. The similarity of the associations between average acceleration and body fatness/physical function with those between MVPA and body fatness/physical function in model 2 is not surprising, given the high correlation between average acceleration and MVPA. Given the independent positive associations between the intensity gradient and physical function, it is possible that the intensity distribution of the physical activity profile may be of particular relevance to frailty, elderly, and/or in rehabilitation. It is likely that for different health and physical function outcomes the relative importance of the average acceleration and the intensity

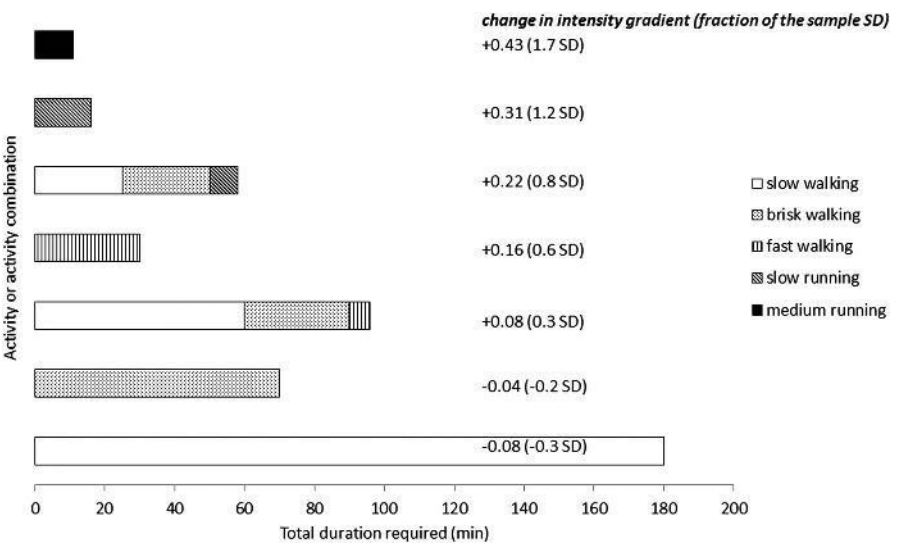

FIGURE 4—Duration per day of activity type(s), all of which increase the average acceleration by 1 SD (sample 2), and the effect of each on the intensity gradient for an example participant (average acceleration and intensity gradient both 1 SD below sample mean).

gradient will differ. The use of these two metrics will enable further investigation of independent, additive, and interactive effects of activity volume and the intensity distribution on health and physical function. Potentially, this could facilitate the incorporation of choice in physical activity promotion messages, allowing individualization of interventions.

The average acceleration and intensity gradient metrics are not immediately interpretable in the way that minutes of physical activity are, but translational outcomes can be produced post hoc using data from calibration studies (e.g., (25,29,31,32,34)). Importantly, this shifts assumptions re-lating to the conversion of acceleration metrics to physical activity intensity outcomes from the analysis stage to the translation of the research. Further, this means that interpre-tation and translation can be updated and/or changed with ease by other researchers; access to the primary data would not be required. We have presented an example translation of the outcomes, highlighting how the recommended time accumu-lated across a range of physical activity intensities per day can be manipulated, e.g., as appropriate for a given health outcome, or as selected as achievable by a participant, or most suited to a given demographic. Translations such as these could be used to develop meaningful physical activity targets, as appropriate, for individuals or groups. As Wolff-Hughes et al. (35,36) have done for total accelerometer counts per day for U.S. adults and children using NHANES 2003–2006 data, it would also be possible to generate age- and sex-specific population-referenced percentiles for both metrics. This would facilitate comparison with norms, comparison of population subgroups (e.g., ethnic groups), and the tracking of physical activity over time (35,36).

Kim et al. (26) recently showed that fatness and grip strength at baseline predicted both average acceleration and total time spent in MVPA at follow-up (median, 5.7 yr; interquartile range, 4.9–6.5 yr) in 993,000 participants in UK Biobank. This is consistent with the cross-sectional associations observed for body fatness in the current study. However, in our smaller data set, neither average acceleration nor MVPA was associated with grip strength, whereas intensity gradient was associated with grip strength. The size of the UK Biobank sample (2) offers considerable scope for exploring potential health and/or performance differences between participants with similar average acceleration levels but very different intensity distri-butions. This could feed into whether physical activity in-terventions and/or public health messages need to focus on volume of activity alone or also on shifting the intensity gra-dient by focus on specific intensities. We have provided examples of how this could occur in the results section.

It should be noted that the validity of the average acceleration and intensity distribution metrics would still be dependent on the procedures used to clean the acceleration signal, e.g., removal of gravity, and detection and treatment of nonwear (23,24). Furthermore, the magnitude of the inten-sity gradient will depend on the size of the intensity bins used to summaries the acceleration data. Rerunning the analyses with intensity bins of 40 mg and 50 mg did not change the pattern of the results but did affect the magnitude the intensity gradient and constant (y-intercept). For consistency, we would recommend standardizing the intensity bin size at 25 mg. This provides a fairly high, but manageable, resolution.

Strengths and Limitations

The current study demonstrates the utility of the proposed metric, the intensity gradient, in two large heterogeneous samples. We only examined data from the GENEActiv accelerometer, but our previous research indicates the same metrics calculated from the Axivity (as used in UK Biobank, Doherty et al. (2)) would likely be equivalent (17). The average acceleration from the ActiGraph (as used in the US National Health and Nutrition Examination Survey (3,15)) is around 10% lower (17,18), but this appears to be consistent across the intensity range (17,37), suggesting that the intensity gradient may be comparable.

Further, we only used data collected at the nondominant wrist. Participants in UK Biobank wore accelerometers on their dominant wrist (2), unlike most other studies that use the nondominant wrist (1,3–7). Average acceleration tends to be higher when measured at the dominant relative to the nondominant wrist (unpublished data from our laboratory). Whether the intensity gradient differs will depend on whether differences between the dominant and the nondominant wrist are spread equally across the intensity distribution. We plan further research to investigate the degree to which average accelera-tion and the intensity gradient differ between wrists.

In summary, the average acceleration and the intensity gradient together provide a complementary description of a person_s entire activity profile and will facilitate investiga-tion of the relative importance of intensity and volume of activity for a given outcome. Crucially, the metrics are not subject to the error and population specificity associated with converting acceleration into physical activity outcomes. They would be appropriate for reporting as standardized mea-sures, suitable for comparison across the wealth of studies using wrist-worn raw acceleration accelerometers.

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