BASES EXPERT STATEMENT

USE OF ACCELEROMETER DATA TO MEASURE AND INTERPRET FREE-LIVING PHYSICAL ACTIVITY

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Accelerometer data have traditionally been expressed as time spent in physical activity intensities using thresholds or cut-points. A move away from cut-points is recommended because of the 'cut-point conundrum' where different thresholds can lead to vastly different estimates of physical activity (see next page), lack of comparability between devices, and inability to capture the multidimensional nature of physical activity. Despite the emergence of alternative approaches, use of cut-points is still widespread. There is therefore a need to de-mystify alternatives to cut-point analyses and provide guidance for researchers and practitioners.

BACKGROUND AND EVIDENCE

What are raw acceleration and counts data? Accelerometers record time-stamped accelerations at high frequencies, which represent the raw acceleration data. Most research-grade accelerometers measure raw acceleration in three orthogonal axes capturing forward/back, side-to-side, and up/down movements of the device. Accelerations are recorded due to movement and the earth's gravitational field, which provides information on the orientation of the device relative to where it is worn. Raw acceleration data need to be processed further to provide meaningful interpretations of physical activity. Traditionally, raw accelerations have been transformed using accelerometer manufacturers' proprietary algorithms into movement counts, which are device-specific dimensionless values used to estimate physical activity. Over the last decade, alternative metrics to counts have been generated from raw accelerations using open-source methods, for example the Euclidian Norm Minus One (ENMO) and Monitor Independent Movement Summary (MIMS)-units[1]. An important advantage of such accelerometer metrics is that they are largely comparable between devices, irrespective of manufacturer or model (Rowlands *et al.*, 2019).

> The existence of different accelerometer metrics and outcomes, and the ability to convert between raw acceleration and counts data creates a confusing picture.

[1]Other accelerometer metrics exist, such as mean amplitude deviation (MAD).

A further step is then required to translate these continuous metrics derived from acceleration data (including counts) into physical activity outcomes. Researchers typically apply cut-points to these continuous metrics to estimate time spent in physical activity intensities. However, a range of other outcomes can be generated that better capture the multidimensional nature of physical activity and which are the focus of this Expert Statement. It should be noted though, that additional information is contained within the raw acceleration signals, such as frequency component and orientation, which can be exploited to generate additional outcomes (e.g., related to posture). These outcomes are beyond the scope of this Expert Statement and will not be discussed further.

THE CUT-POINT CONUNDRUM

Physical activity estimates derived from cut-points are prone to bias and intensity misclassification (Trost, 2007). This is because cut-points are specific to the population of interest, the protocols and samples used in the original cut-point calibration, and in the case of counts, the accelerometer device and manufacturers' count algorithms which historically were typically unknown. Applying different cut-points to the same accelerometer data can lead to vastly different estimates of physical activity. For example, it has been reported that the prevalence of children achieving the recommended 60 minutes of moderate-to-vigorous physical activity (MVPA) per day varied from 8% to 96% (Migueles *et al.*, 2019) depending on which cut-points were applied. This severely thwarts determination of people meeting physical activity guidelines, seriously impacts translation of research to public health priorities, and confuses understanding of relationships between physical activity and health outcomes. Therefore, to avoid misinterpretation of results it is vital that care is taken when selecting cut-points and reporting methods and outcomes. Further, it is imperative that cut-points are appropriate for the device wear-site (e.g., wrist versus hip) and population, and that between-study comparisons use the same cut-points.

ALTERNATIVE APPROACHES

A range of additional alternative accelerometer outcomes are available that avoid or reduce the impact of the cut-point conundrum and allow exploration of the multidimensional nature of physical activity (Table 1). Such outcomes can be reported in isolation but are often complementary and can provide a comprehensive and nuanced representation of physical activity. They can be categorised as single value summary, time-use, and patterning outcomes.

- Single value summary outcomes: These provide a top-level overview of physical activity over the measured period (e.g., the whole day) and are useful for tracking changes over time and understanding associations between physical activity and health. The combination of physical activity volume and intensity is more predictive of health outcomes, than either alone (Rowlands *et al.*, 2018).
- Time-use outcomes: Accelerometer data are split into incremental intensity bins and the time spent in each bin is calculated. These can be multiple high-resolution bins (i.e., the intensity spectrum approach (Migueles *et al.*, 2021)), or a small number of wide bins (e.g., inactivity, light intensity physical activity, MVPA) reflecting traditional cut-points.
- Patterning outcomes: Patterning can be expressed in different ways. These include whether physical activity is accumulated sporadically or in bouts, fragmentation (e.g., probability of transitioning between inactive and active states), and the intensity of the most physically active accumulated minutes or continuous periods of the day.

▼ **Table 1:** Summary of accelerometer metrics.

	Outcome type	Software	Method/Outcome	Definition	Interpretation/example applications
Single summary value	Volume	Open Source[1] Proprietary[2]	Average acceleration Total counts/day Counts/min	Proxy for volume of PA accumulated over a specified time period (e.g., school day).	Track change over time. Emerging data will allow comparison to age and sex-referenced norms.
	Step count	Open Source[1] Proprietary[2,3]	Total steps/day	Proxy for volume of PA, expressed as steps, accumulated over a time period (e.g., school day).	Easily understood proxy of physical activity volume. Use caution when comparing steps between studies as devices use different methods to identify a 'step' from acceleration data.
	Intensity distribution	Open Source[1]	Intensity gradient	Describes relationship between physical activity intensity and time accumulated at that intensity.	Assess relative importance of volume and intensity of PA for health Emerging data will allow comparison to age and sex-referenced norms.
Time-use	Time in incremental intensity bins	Open Source[1]	Intensity spectrum	Time spent in a wide range of high-resolution intensity bins over a time period (e.g., 24-h).	Identify intensity(ies) that have strongest associations with health outcomes.
	Time in pre-specified intensities	Open Source[1] Proprietary[2]	Cut-points	Time spent in physical activity intensities over a time period (e.g., minutes of MVPA/day).	Prevalence of meeting PA guidelines. Specifying the composition of time-use across the 24-h day.
Patterning	Bouts	Open Source[1] Proprietary[2]	MVPA accumulation (bouts / sporadically)	MVPA reported separately according to whether or not it was a pre-defined bout (e.g., 5-min, 10-min).	Investigate whether MVPA accumulation differs between groups and/or relates to health outcomes.
	Fragmentation	Open Source[1]	e.g., Active to Sedentary Transition Probability[4]	The probability of transitioning from an active to a sedentary state. Calculated as the reciprocal of the average fragment duration.	Marker of declining functional status in older adults.
	Most active accumulated minutes	Open Source[1]	MX accumulated	Amount and distribution of intensity across the day. The intensity above which someone's most active X minutes are accumulated. (e.g., M1 represents the most active 1-min accumulated across the day).	Illustrates patterns of daily activity underlying the single summary metrics.
	Most active consecutive minutes	Open Source[1]	MX continuous	Timing and intensity of the most active X continuous periods of the day. (e.g., M10 is the most active 10 continuous minutes).	Investigate whether timing of activity is associated with health (e.g., active in the morning or evening)

[1] E.g., GGIR R-package to process multi-day raw accelerometer data for physical activity and sleep research (Accelting, Almere, The Netherlands)
[2] E.g., Actilife (ActiGraph LLC, Pensacola, Florida)
[3] Actilife software uses an algorithm to classify steps rather than generating them from counts.
[4] A range of other fragmentation metrics also exist. A brief list can be found here: https://cran.r-project.org/web/packages/GGIR/vignettes/GGIR.html#573_Fragmentation_metrics
PA: Physical activity; MVPA: moderate-to-vigorous physical activity.

RESEARCHER DATA COLLECTION AND PROCESSING CONSIDERATIONS

While accelerometers remove the subjectivity and sources of measurement error associated with self-report methods, there are still several researcher decisions which influence accelerometer outcomes. Decisions relating to device type, wear location, wear protocol, wear time criteria, sampling frequency, epoch interval, and other data processing functions should be driven by the research questions of interest and be clearly reported. These researcher decisions allow scope for accelerometer data to be collected, processed, analysed, and reported in a variety of ways, therefore transparent and detailed reporting of methods is essential. Moreover, researchers also need to be aware of considerations and resources needed that will impact the practical and time aspects of their accelerometer data processing and analysis. These can include computer data processing power, data storage capacity, and post-processing steps needed to prepare data for analysis.

APPLICATION AND INTERPRETATION OF ACCELEROMETER OUTCOMES

Open science principles allow anyone to access non-proprietary accelerometer data processing and analysis tools. Researchers can generate a wide range of accelerometer metrics, outcomes, and visualisations using freely available R packages including:

- GGIR (https://cran.r-project.org/web/packages/GGIR/index.html)
- MIMSunit (https://cran.r-project.org/web/packages/MIMSunit/index.html)
- acc (https://cran.r-project.org/web/packages/acc/).

Open-source methods allow conversion of raw acceleration data to ActiGraph counts to enable comparisons with historical studies (e.g., https://github.com/bhelsel/agcounts). Reference values (Fairclough *et al.*, 2023; Rowlands *et al.*, 2021) and visualisation tools to aid interpretation of raw acceleration metrics are also emerging (Schwendinger *et al.*, 2024). However, to reduce barriers to uptake there is a need for accessible training and development for researchers to learn about and implement open-source methods. Critically, such resources need to be as user-friendly as possible to empower more researchers to engage with confidence.

CONCLUSIONS AND RECOMMENDATIONS

Physical activity is multi-faceted and use of multiple outcomes to describe volume, intensity, and patterning can provide a nuanced picture of this behaviour. However, the existence of different accelerometer metrics and outcomes, and the ability to convert between raw acceleration and counts data creates a confusing picture. This Expert Statement goes some way to elucidate the issues and provides guidance and signposting for researchers and practitioners working with accelerometers. With this in mind, we provide summary recommendations for researchers below to help with standardising the reporting of accelerometer data.

1. To enable appropriate comparisons between studies and aid transparency, report all methodological and data processing decisions (e.g., device, wear-site, sampling frequency, accelerometer metric, epoch size, outcomes, cut-points (if used), etc).
2. Include a summary single value outcome that describes physical activity volume and/or intensity. Age and sex-specific reference values are emerging to aid interpretation.
3. Include at least one descriptor of time-use and/or patterning (e.g., time spent in different intensities, intensity of most active periods, etc). ■

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