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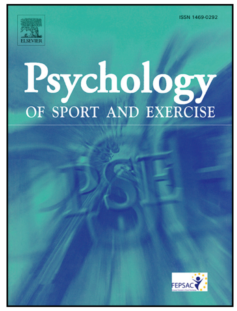

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Assessing Physical Behavior through Accelerometry – State of the Science, Best Practices and Future Directions

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Title: **Assessing Physical Behavior through Accelerometry – State of the Science, Best Practices and Future Directions**

Abstract [296 words]

Accelerometers offer opportunities for researchers to capture valid data about the intensity and amount of physical behavior (PB) in real-time over a period of several days and weeks. From this multidimensional data, a great number of metrics can be derived to capture and describe the unique aspects of PB. The goal of this paper is to help the end-user of PB monitoring devices (novice to intermediate experience) wade through sometimes excessive technical details of accelerometry to outline best practices in selecting and applying devices to quantify three major behavioral categories of common interest to the research community: physical activity (PA), sedentary behavior (SB) and sleep. The effects of these decisions on the metrics (energy expenditure, activity intensity, body position, activity patterns) can occur in a variety of ways. The device, carrying position (hip, wrist, thigh) and recording parameters (epoch length, frequency, memory capacity, recording frequency and filters) have a large influence on the measured activity. The different backgrounds such as study design (purpose, repeated measurements) and duration (time frame, wear time) as well as data storage and evaluation must be taken into account when determining the parameters. Finally, the evaluation must adjust several levers (raw data, context information, non-wear time, intensity classification, compliance) depending on the target variables. Looking into the future, current developments in statistical analysis are discussed, because the research community has not yet reached a consensus on the most promising approach. There are exciting developments ahead of us in the future. Sleep in particular is increasingly being seen as an influencing factor for health. Together with the technical developments in sensors which will become incrementally smaller, more accurate and in the near future will be integrated directly into our clothes or skin, accelerometry is facing exciting times and lots of data to evaluate.

Assessing Movement Behavior through Accelerometry – State of the Science, Best Practices and Future Directions

State of the Science

In the 40 years since Montoye's team of exercise physiologists and engineers modified a phono cartridge to measure bodily acceleration (Wong et al., 1981) and predict the energy expenditure of physical activity (PA) (Servais et al., 1984), device-based measures of PA and related behaviors have emerged as an essential tool for PA and health promotion research. Indeed, the team's prescient observations that "the accelerometer's greatest value may be in the area of categorizing people into various activity-related groups. It could also be used as a device by which people could compare their daily activity to a prescribed level for rehabilitation, weight loss, or personal goals in training" (Servais et al., 1984, p. 170) has become fully realized in recent years. PA monitoring devices continue to be a leading fitness trend (Thompson, 2018) and more than 100 million tracking devices and accelerometer enabled smart watches were sold in 2017-18 (Lamkin, 2018). Activity monitors have emerged as important self-monitoring tools in clinical medicine (Lobelo et al., 2018) and large-scale health promotion (U.S. Department of Health and Human Services, 2018) and are now commonly used in national surveillance efforts (Burchartz et al., 2020; Colley et al., 2011; Matthews et al., 2008; Troiano et al., 2008). The number of yearly publications by search terms 'exercise or physical activity' and 'acceleromet*' rose from 10 or fewer until the year 1996 to over 600 in the years 2012 and 2013 (Troiano et al., 2014). The same search term yields more than 1,200 publications on scopus.com in 2019 (assessed on 7th November 2019).

One of the advantages of accelerometry is that it can collect dense data over a long period of time (days, weeks and sometimes even months) allowing a detailed examination of daily behavior. From this multidimensional data, a great number of metrics can be derived to capture and describe the unique aspects of movement behavior (MB). Results from recent epidemiologic studies are providing new insights into the distinct influence of sedentary behavior (SB), light (LPA) and moderate-to-vigorous intensity physical activity (MVPA) on health enabled by accelerometry (Diaz et al., 2017; Matthews et al., 2016), and new cohort studies are using accelerometers on a much larger scale and include the assessment of sleep (Doherty et al., 2017; German National Cohort Consortium, 2014). This accelerometer era in MB research might be considered a golden age with vast opportunities, but many challenges remain.

Although there are suitable and precise devices available for most applications (e.g., interventions, epidemiology, surveillance), the wide variety of devices and prediction algorithms available for a variety of metrics (e.g., step counts, energy expenditure, intensity classification, posture, sleeping pattern) and limited information from rigorous validation studies make it difficult for the average user to understand what the most appropriate options are for individual application. One device may not fit all applications, and users must make informed choices to optimize the outcomes for individual studies. The goal of this paper is to help the end-user of MB monitoring devices (novice to intermediate experience) navigate through sometimes excessive technical details of accelerometry to outline best practices and highlight necessary considerations in selecting and applying devices to quantify two major behavioral categories of common interest to the research community: PA and SB. Although sleep is an increasingly important behavioral category, it is only mentioned in extracts, as the authors of the article have little practical experience in recording sleep.

Throughout this paper, no major distinction is made between accelerometers sold for research purposes (research devices) and those sold to the general population (consumer-devices), it is expected that the decision-making processes apply to each. In many instances, consumer-devices are as accurate as research devices and they often provide feedback to participants more easily (Henriksen et al., 2018; Wahl et al., 2017). Nonetheless, consumer-devices rarely provide raw data and mostly use proprietary algorithms, which make the harmonization of various dataset difficult. In addition, a reanalysis of the data with different calculation methods is almost impossible with proprietary algorithms.

The opinions outlined in this article reflect the accumulated experience of the authors with a wide variety of monitoring devices. The group of authors consists of inter-disciplinary researchers in the field of accelerometry and MB as well as device developers that came together at the 2nd

International Workshop for the Center for the Assessment of Physical Activity (CAPA) held on the 11th and 12th of July 2019 at the Karlsruhe Institute of Technology, Germany. This is not a systematic review but rather reflects the authors' expert consensus on the topic of accelerometry for MB assessment.

The following section focuses on best practices and is divided into subsections of:

- Behaviors, highlighting the differences in assessing the different facets of the MB spectrum
- Metrics, providing insight on what parameters to use for different goals,
- Study Design, showing differences in approaches for a variety of research questions,
- Data collection, processing and (storage/accessibility), describing what still needs to be done after the study has been designed,
- And current developments in statistical analysis, highlighting the need for sophisticated methods to analyze data.

The last section will focus on future directions of the field. Some of these directions are already developing; others will definitely be important topics in the future.

Although there is literature that provides help for users of accelerometer-based measures in surveillance (Pedišić & Bauman, 2015), which gives considerations regarding data collection and processing (Migueles et al., 2017) or focusses on methods in intervention studies (Montoye et al., 2018), the need for directions for new researchers in this field still exists. The authors provide these directions and related useful references to help practitioners and researchers when considering using accelerometers.

Best Practices

Currently, accelerometry is the "state-of-the-art" when it comes to device-based measurement of MB. Besides PA, SB and sleep are the most common behaviors assessed via triaxial movement acceleration methods within 24-hour measurements.

Behaviors

Physical activity

"Physical activity is defined as any bodily movement produced by skeletal muscles that results in energy expenditure" (Caspersen et al., 1985, p. 126). When Caspersen and colleagues defined PA in 1985 accelerometers where not yet feasible and widely available for PA assessment. Technological advances created increasing interest in using accelerometry for assessment of PA today (Ward et al., 2005; Welk, 2002) using different outcomes (see Metrics for more information). The main advantage of using accelerometry over self-reported (retrospective) PA is that it is not prone to recognition, memory or social desirability biases of participants as recall measures are (Adams et al., 2005; Brenner & DeLamater, 2014; Nigg et al., 2012). A detailed discussion of the questionnaire approach can be found in the Physical Activity Questionnaire Paper (Nigg et al., this issue). A review on the comparison of indirect (i.e. questionnaires) and direct, device-based measures of PA in pediatric populations revealed 72% of indirect measures overestimated the directly measured values (Adamo et al., 2009). This trend, however, was neither confirmed for adults (Prince et al., 2008), nor for older adult populations (Kowalski et al., 2012). Here, no clear patterns emerged for the mean differences between subjective self-report and device-based measures of MB. Moderating factors of overestimations are less clear and need to be examined in future studies. In general, correlations between device-based and self-report measures are weak across the lifespan, showing a discrepancy between both measures. However, the need for device-based monitoring of PA, ideally 24 hours a day, for assessment of real-life activity patterns is often stated.

Sedentary behavior

Besides PA, it is also important to objectively measure SB (Lewis et al., 2017), especially since studies have shown that SB has negative effects on health outcomes (Katzmarzyk et al., 2019). According to the internationally accepted definition of SB (Tremblay et al., 2017), it is necessary to capture both characterizations of SB, namely: body posture (sitting/lying/reclining) and energy expenditure (≤ 1.5 MET). Moreover, there is an ongoing debate on whether the effects of SB on mental and somatic health are independent from PA or not (Biswas et al., 2015; Ekelund et al., 2016). Thus, there is a growing need to assess both behaviors during a specified time frame and separate them during analysis.

Sleep

The effects of PA, SED, and sleep are examined by most researches in isolation (Chaput et al., 2017). what is flawed because time spent in one behavior will naturally depend on the composition of the rest of the day (Taylor et al., 2018). Even if less established than PA and SB measurement, accelerometers can also be used to assess sleep, which is the third component of every day MB. Different sleep quality patterns, like bed and out-of-bed time (and therefore hours per day spent in bed) and nighttime movements or even clinical sleep issues can be assessed. But this 24-h movement recording require different methods of data analysis than standard multivariate techniques. These methods need to take into account the co-dependence and proportional nature of compositional data (Chastin et al., 2015). A study comparing sleep/wake judgements obtained via sleep diaries and accelerometers revealed good agreement for nocturnal sleep (Kawada, 2008). Similar findings were obtained by a recent review on validity and reliability of sleep time questionnaires across the lifespan with moderate to strong correlations between measurements (Nascimento-Ferreira et al., 2016) as well as in a study combining both, diaries and questionnaires with accelerometer data (van Hees et al., 2015). When validated against polysomnography, the state-of-the-art method for sleep screening, high correlations can be detected, revealing accelerometry to be a good tool for real-life assessment (Jean-Louis et al., 2001).

Metrics

Accelerometry is based on continuous and real-time measurement and recording of movement-induced raw acceleration signals over a specific period of time (epoch length). Accelerometers register intensity and duration of single- or multi-axial accelerations and convert this raw data into manufacturer- and model-specific outcome metrics. Before the raw data is converted, it is usually filtered. This should eliminate acceleration frequencies that are not compatible with human movement. Most devices allow the user to choose between different filters when processing the data. As the different filters have a large impact on the outputs it is important to report information on the filters used.

Unfortunately, there are no internationally accepted standards for signal processing (Ann V. Rowlands, 2007). Due to these differences in raw data processing and filtering, outcome metrics cannot be directly compared across devices (Chen & Bassett, 2005). However, using identical software and algorithms to process outcome measures can help in harmonizing data. A recent study by Alex V. Rowlands, Mirkes et al., 2018 has shown that key physical activity outcomes derived from data of different devices, that were processed identically afterwards, were largely equivalent.

Since the outcome metrics provided by accelerometers is without direct physical meaning, it has to be translated into a more interpretable unit or measure (Troiano, 2006). For Example, different age-specific cut-points can be applied to accelerometer outcome metrics in order to express raw data in terms of time spent in specific behaviors (PA, SB or sleep), in different positions and postures (standing, sitting, lying), and to determine intensities of PA (low, moderate, vigorous; e.g., Schaefer et al., 2014). When applying specific cut-points from calibration studies it is crucial to follow the same data collection protocol (processing, epoch-length, device placement, filter, etc.) which was used in the original study (Migueles et al., 2017, p. 1842). Although common metrics of interest are described in detail in this section, there are new approaches that focus on improving these existing metrics. Finding metrics for PA volume and intensity that are derived from raw acceleration has been the focus of recent studies and shows great promise. (Alex V. Rowlands, 2018; Alex V. Rowlands, Edwardson et al., 2018; Alex V. Rowlands, Fairclough et al., 2019)

Energy expenditure

One key use of accelerometry is to interpret the raw data recorded by the device for estimating energy expenditure (EE). This is one way to make accelerometer data comparable across different types of PA and over a broad range of target groups. Therefore, accelerometer metrics often are transferred into the commonly used metabolic equivalent of task (MET). The obtained MET values can then be categorized into sedentary (≤1.5 METs), low (1.5-3 METs), moderate (3-6 METs), and vigorous (>6 METs) PA (Butte et al., 2012) for adults. Children however are known to have considerably higher basal metabolic rates per unit body mass than adults. Therefore, adult MET-thresholds do not apply to them (McMurray et al., 2015; Saint-Maurice et al., 2016). For scoring and interpretation of youth physical activity data, the new Youth Compendium of Physical Activities can be applied (Butte et al., 2018).

When interpreting accelerometer data by means of energy expenditure one has to consider that multiple different algorithms to convert accelerometer outcome metrics into EE outcomes exist. This may lead to different EE outcomes depending on the algorithm used so that one cannot directly compare data from different accelerometer models if the converting algorithm is not open to the public. Furthermore, the relationship between a specific activity and EE can vary due to external circumstances (additional loading, changes in altitude, temperature). Moreover, depending on placement, accelerometers are not capable of accurately detecting the intensity of activities involving the use of upper extremities and activities with limited hip movement (Prince et al., 2008).

The inclusion of heart rate monitors may be of additive informative value, especially in activities involving isometric muscular contraction such as weight-bearing exercises and activities such as carrying a load, pushing, and rowing (Jakicic et al., 2004; Kozey Keadle et al., 2010). A combination of accelerometer analysis and heart rate monitoring may further improve the overall accuracy of energy expenditure and exercise intensity assessment in free-living situations.

Activity Intensity

The volume and intensity of PA and SB during a specific time interval (hours, days and weeks) may be obtained by classifying outcome metrics accumulated in a specific epoch length (integration of a filtered digitized acceleration signal over a user-specified time interval, more later in Data collection) with a set of cut-points. These cut-points function as thresholds for outcome metrics and are used to categorize activities as sedentary, light, moderate, vigorous or very vigorous activities (Migueles et al., 2017).

These cut-points are generally validated specifically for a certain model of accelerometer, wear location, age group, and health status of the observed population (Taraldsen et al., 2012). Thereafter, applying cut-points to a specific data set requires following the same data collection and processing criteria that were applied in the original calibration study.

Body position and posture

Some accelerometers have the ability to distinguish between different body postures and positions using the inclination output from the accelerometer. By using both inclination and dynamic acceleration, these devices are able to classify basic posture by distinguishing sedentary activities from upright activities. The ability to identify different body positions and postures is reliant on the placement of the accelerometer on the human body (e.g. hip, wrist, thigh etc.).

However, Carr and colleagues (2012) reported that the correct body position was identified in only two-thirds of the time during sedentary activity. This may be attributed to the fact that accelerometry analyzes MB in predefined epoch lengths (Ayabe et al., 2013). Especially small activities such as transitions from a sitting or supine position only last a few seconds and thus may be below the epoch length chosen and are therefore not resolved. New methods to address this using angle for posture estimation show promise (Vähä-Ypyä et al., 2018).

It is also challenging to monitor the MB of certain study populations like toddlers, children and people with movement disabilities due to the occurrence of “non-standard” postures, such as kneeling and crawling (Davies et al., 2012). These postures are “non-standard” because the devices categorize body position as either sit/lie, stand, or step. The best way to quantify non-standard postures and the transitions between postures is direct observation or proxy reporting. Additionally, time spent in a posture does not indicate the effort someone must exert to attain or maintain this posture or movement.

Activity patterns

To date, the majority of research has focused on associations between the amount of time spent in SB, LPA and MVPA and health. However, recent evidence from controlled experimental trials suggests that the pattern of MB may also be related to health outcomes, even when accounting for the total volume of activity (Keadle, Sampson et al., 2017). Apart from MB variables like duration, intensity and volume, activity pattern has been suggested as a MB outcome that may provide additional information beyond reports of activity counts or other outcome metrics (Cavanaugh et al., 2010). Especially short PA breaks between prolonged periods of SB are important to reduce the adverse somatic and mental health effects (Ekelund et al., 2016; Giurgiu et al., 2019). Thus, determining these intermissions is of relevance especially in organizational settings such as worksites and schools. In the current literature, the term bout is often used to describe a predefined amount of time without intermission in the same MB. However, with the emerging new possibilities of data analysis the term "activity pattern" refers to more than just the summation of bouts.

Another very interesting measurable characteristic is the timing of different MB. Olds et al. (2011) got results that associated late bedtimes and late wake up times with an unfavorable activity and weight status profile. Matricciani et al., 2019 used GENEActive wrist-worn accelerometers to check for sleep duration, onset, offset, day-to-day variability and efficiency. Recent studies used accelerometer to assess associations between sleep duration, timing and regularity with measures of adiposity (Zhou et al., 2018) or physical activity (Xu et al., 2019).

The development of population independent outcome metrics that appropriately assess prevalence of meeting MB guidelines is another new approach to quantify accelerometer outcomes. Metrics like "magnitude of acceleration above which a person's most active 60 (for children) or 30 (adults) minutes are accumulated" are possibly comparable across datasets and a new tool for public health to report on guidelines (Alex V. Rowlands, Sherar et al., 2019).

Evaluating the Accuracy and Precision of outcome metrics

Somewhat surprisingly, it can be difficult to determine the accuracy and precision of monitoring devices in the setting it is typically used in—in population-based samples of free-living individuals about their daily life, at home, work/school, or in leisure-time. If one is interested in only assessing the total volume of PA, estimated as total activity counts or a sum of all bodily acceleration during the monitoring period, then less validation work may be needed. On the other hand, if you want to know the true validity of your estimates of step counts, sedentary time, EE or the duration of activity intensities or sleep, more rigorous validation studies are needed. For example, validation of EE can be performed by validating against oxygen intake determined by spiroergometry.

It has become clear that the initial assumption that simple calibration studies using laboratory-based approaches alone would be sufficient to develop accurate prediction algorithms for MB in real life settings was not always tenable. Prediction methods developed using only a small set of activities in controlled environment have not always produced valid estimates of the target behaviors in real life because they cannot cover the whole spectrum of MB that occurs. Additionally, high quality validation studies (described in more detail below) are actually relatively rare, especially with the use of free-living data. Many new prediction methods have been created, but few have been tested rigorously. Limited information about which of these prediction methods (e.g., moderate-vigorous intensity cut-points, Lee et al., 2019) are most accurate have led to much confusion in the field. To help clarify this area, and to identify studies that may provide better estimates of validity, Keadle and colleagues (2019) have recently proposed a framework outlining specific steps in the monitor development, calibration, and validation process. Drawing on frameworks employed for drug development, they proposed four phases of monitor development, validation, and application. The initial step (Phase 0) relies on bench testing and refining the technical reliability of the monitor. The next steps reflect monitor calibration or development of the prediction algorithms. Phase I testing includes simpler and more controlled laboratory-based testing of selected activities using fixed start/stop times and development of initial prediction method(s). Phase II testing extends the earlier phase and includes implementation of semi-free-living protocols including transitions between activities to further develop and refine prediction methods. Criterion measures such as direct observation and indirect calorimetry are integral to monitor calibration process, and these data are often used to provide initial validity information about new devices or prediction methods. However, since the data employed in these “validation” studies are derived from the same study population from which the prediction methods were developed, they may overestimate the actual validity of the method, when it is applied in a new study population. Phase III of the development process involves rigorous validation studies of previously developed prediction methods using strong criterion measures (i.e., indirect calorimetry, direct observation, doubly labelled water) in a study sample different from that used to develop prediction method (i.e., independent sample). Examples of strong Phase III validation studies include that of Toth and colleagues (2018) who evaluated the validity of step counts from a variety of devices in comparison to video direct observation; Lyden and colleagues (2014) who evaluated estimates of MVPA using a new machine-learning algorithm in comparison to direct observation; Chomistek and colleagues (2017) who compared a variety of ActiGraph prediction methods for energy expenditure to doubly labeled water; and Crouter et al. (2013) who compared estimates of MVPA duration using several ActiGraph prediction methods to indirect calorimetry. Implementation of strong criterion measures in independent samples of free-living individuals can provide clear evidence for most accurate precise methods, while reliance on Phase I/II can be useful but leaves much more uncertainty. Unfortunately, Phase III validation studies in most cases are relatively rare and only Phase I or II studies are available to evaluate a method of interest.

The final phase (Phase IV) of the development process involves application and dissemination of methods that have successfully progressed through previous phases. As data processing and prediction algorithms become more complex, to minimize the requirements of specialized expertise, development of more user-friendly methods will be required for more effective dissemination and use by the research community.

Limitations/Perspectives

The accelerometry data should be both directly comparable and understandable in physical terms and valid over a broad range of target groups (Taraldsen et al., 2012). Unfortunately, only little data is available to provide evidence to determine the most valid variables for different purposes.

A common problem with all acceleration monitors is processing and classifying the data into MB outcome variables. Specifically, different methods for handling the same data can result in significantly different values for the same outcome variables. Thus, although MB measurement with accelerometers may be considered “objective”, there are subjective elements such as setting the epoch length and cut points, and consensus guidelines for collecting and processing these device-based measured data are lacking (Heil et al., 2012). Furthermore, contextual information related to the setting and type of activity in accelerometry is limited. Thus, information from other sources (i.e. behavior logs) and sensors should be integrated to better understand MB in different contexts and to increase the measuring comparability by imputing non-weartime (Sprengeler et al., 2017). This however will increase participant burden as well as evaluation effort from researchers.

Study Design

Choosing a monitor and monitor placement

Choosing the “best” monitor for a given research, clinical, or intervention application depends on the characteristics of the MB one wants to measure; the type of study or intervention project at hand; the amount of burden that participants might accept; and the staff and resources available to administer the monitors. These resources include cost of the devices, logistics of monitor administration, data storage and analytic resources available, and increasingly specialized expertise to implement more advanced prediction methods/algorithms.

The first question to ask when deciding on which monitor to use in a given setting and where to locate it on the body is—what aspects of human behavior and ***metrics*** from those behaviors should be measured? Different monitoring devices have different strengths and weaknesses for predicting different summary metrics. For example, thigh worn devices generally provide more accurate and precise measures of body posture than do waist- or wrist-worn accelerometers, although devices worn at each of these sites may output a summary metric for sedentary time. Additionally, there can be important differences in the accuracy and precision of a given metric—even when they are derived from the same type of monitor. For example, more advanced pattern recognition methods are likely to be more accurate and precise than simple cut-points derived from the same device (Lyden et al., 2014). It is recommended to think about identifying the most valid algorithm to predict the specific metrics of interest, and then select the monitor and monitor placement that can capture data to feed into that algorithm. In other words, identify the summary metrics of primary importance for the study, select the monitoring device and placement that has adequate validity for the specific study population and study type. These choices also need to fit within the resources available for the project and be within an acceptable range of burden for the participants.

Measurement time frame

The time frame for data collection depends mainly on the research question, or the broad measurement objective. In planning a study, researchers have to decide how long the monitors should be worn each day (e.g., a few hours, waking day, 24-hours), how many days the data collection period should include, and whether seasonal variation in behavior may affect the results (Atkin et al., 2016; Matthews et al., 2001). Choosing a device or prediction method that has higher validity/accuracy should minimize systematic errors in the estimation of the PA metrics of primary interest. However, human behavior is inherently variable because humans are not robots that do exactly the same thing every day. This result in a natural day-to-day variation in behavior and our patterns of behavior often change with the seasons and from one year to the next. Thus, natural variation in behavior must be taken into account when designing measurement protocols and matching the protocol with the broad objectives of the study. Study designs with shorter measurement time frames with a goal of estimating mean values within a study population (vs. individual prediction), such as population surveillance and intervention studies, may be more susceptible to the influence of seasonal variation and the measurement schedule may need to be designed to minimize these effects. Short data collection periods within the day might be useful if the research aim is to measure the PA behavior in a specific setting or situation such as during physical education in schools. The waking day, or time out of bed, is often used for studies of SB and PA, while a 24-hour protocol is needed if sleeping behavior is part of the research question as well. In addition, wearing the device for 24 hours increases recording time as well as wear time compliance, thus a recording time of 24 hours per day is recommended when possible (Migueles et al., 2017; Tudor-Locke et al., 2015). However, from an ethical perspective it should be reconsidered carefully if a 24 hours measurement period is justified if only daytime data is of interest.

In terms of the number of days of monitoring needed, this choice may depend on the study objectives. If the goal is to estimate mean values in a population for surveillance purposes, in theory only a single day of observation is needed. Migueles and colleges (2017) recommend a minimum of four days of valid data (wear-time of at least 8-10 hours per day), while Trost and colleagues (2005) claim that MB patterns can be determined with only 3-4 days of measurement with over 80% reliability. The general recommendation to capture seven consecutive days of data collection is typically a feasible approach for assessing habitual MB patterns in children and adults (Addy et al., 2014; Barreira et al., 2015; Trost et al., 2000). Sampling 7-day periods increases the chance of capturing an adequate number of valid days, meaning a compromise between sample size and reliability (Migueles et al., 2017), for meaningful data analysis and it enhances the opportunity that week and weekend days are part of the data collection period (Addy et al., 2014; Trost et al., 2005). Interestingly, Wolf-Hughes and colleagues (2016) noted that purposeful sampling of weekend days can lead to biased estimates of population mean values compared to random sampling, raising questions about the common practice of requiring fixed numbers/types of days in our analyzes. There may be no right or wrong approach and for some purposes including participants with only a single day of observation is appropriate, while studies with other goals may need to ensure more days and specific types of days should be included in the analysis.

The research community has carefully examined the number of days or observation required to achieve adequate reliability for short-term measures (e.g., ICCs > 0.8). However, less work has been done to understand variation in behavior from one administration period (e.g., one 7-day period) to the next. In general, studies that examined this type of variation in behavior have observed relatively high reliability from one 7-day administration to the next in older women from the United States (Keadle, Shiroma et al., 2017) and middle-aged and older adults in Germany (Jaeschke et al., 2018), indicating that 7-day administration periods reflect relatively long-term average values for PA and SB in the population.

Interestingly, behavioral variation in measures, conceptualized as random fluctuations around long-term average behavior (i.e., random measurement error), has a differential impact on statistical results depending on whether the MB variable is used as a dependent or independent variable in models (Hutcheon et al., 2010). When MB variables are used as dependent variables, random error results in no bias in the model-based estimates, but does reduce their precision (i.e., standard errors increase). In contrast, when the MB variables are used as independent variables in our models, random error can introduce bias into the model-based estimates of association (i.e., attenuated beta coefficients) – a phenomenon called regression dilution bias (Elliott et al., 1990). This effect should be considered when interpreting analysis including an independent MB variable.

Studies with Repeated Measurements

Study designs, like interventional or longitudinal studies, that require repeated measurements need some additional considerations in the planning stages to enable the best comparability of the device-based measured MB data collected over time. The monitor administration methods, including wearing position and periods, as well as device settings (e.g. sampling frequency) should remain as consistent as possible within each administration period. Additionally, the wear time determinations and metric prediction methods applied to the raw data should be consistent over time. Furthermore, external factors which could influence the MB, but that are not part of the research question, should be standardized by consistent and purposeful sampling over time. For example, sampling MB with attention to season of the year and/or the days of the week monitored is important to minimize variation due to these factors. A documentation of all procedures and decisions made is recommended, e.g. in form of a standard operation procedure (SOP).

Measurement Reactivity

Wearing an accelerometer might influence the behavior of the participants which is known as measurement reactivity (Baumann et al., 2018). Studies showed that participants modified their PA pattern by the presence of an accelerometer. For instance, in an adult sample a small portion of SB was changed to LPA. In another study, Clemes and colleagues (2008) compared step counts of participants that knew they were being tracked with those of participants that did not know and found a significant increase in the first condition. Devices that display the archived activity or sedentary time might even enhance the effect and motivate participants to change their behaviour. However, if the typical activity behavior should be measured, a modification of the normal activity pattern is not wanted and could bias the results. Therefore, it is recommended to give only as much information as necessary about the outcome measure (e.g. explaining “measuring activity” rather than “measuring steps” or “measuring movement at the hip”) and use devices which do not display any results to reduce the bias of measurement reactivity. Furthermore, longer measurement periods as well as the exclusion of the first measurement day from data analysis can counteract bias due to measurement reactivity (Dössegger et al., 2014).

Data collection and processing

It is critical to document all technical decisions for comparison purposes.

Data collection

Three decisions need to be made before collecting accelerometer data.

First, it is a basic requirement to measure and store the accelerometer raw data. In contrast to previous decades that required accumulating data in formats like counts, the storage capacity of accelerometer devices is not limited as emphasized ten years ago (Ann V. Rowlands & Eston, 2007). The storage of raw data enables researchers to process the data offline with different algorithms (analyzing body position with static components, time course of the magnitude of activity, time-frequency analyzes) or to reanalyze the data with algorithms newly developed in future. The measurement range (e.g. +/-8g) and resolution (e.g. 0.01 g respectively 0.1 m/s^2 per bit) depends on the characteristics of the Micro-Electro-Mechanical Systems (MEMS) sensor selected by the manufacturer of the accelerometer and covers usually the full range of naturally occurring human acceleration values. Sampling frequency (defining the temporal resolution) must be at least twice as high (Nyquist Frequency or Nyquist-Shannon sampling theorem (Shannon, 1949)) as the highest movement frequency component to avoid aliasing effects (this means generating virtual frequency components when the analogue accelerometer signal is digitized). Human movement frequencies can reach values of 10 Hz in writing (Teulings & Maarse, 1984) or 10.5 Hz in piano playing (Furuya & Soechting, 2012). Considering these two examples, a sampling rate of 21 Hz (2 x 10.5 Hz) is required to assess the movement frequency. For the assessment of MB, a sampling frequency of 30 Hz normaly meets the Nyquist criterion. If the magnitude of the activity or the movement pattern (e.g. for biomechanical analyses) is in the focus of interest the sampling rate must be multiple times higher, whereas the accuracy of the measured pattern increases with sampling rate (accuracy – sample-rate trade-off; e.g. a sampling rate of five or ten times higher than the movement frequency results in a more or less amount of distortion of the measured signal. Therefore it depends on the research question how precisely a movement pattern should be measured, respectively which grade of distortion is acceptable to increase measuring time (depending on the storage capacity of the device). Kang & Rowe, 2015 developed a method for an automated, task specific optimisation of sampling rates.

Secondly, like mentioned before it needs to be decided how many days or weeks need to be measured. This decision mainly depends on the study question (for a detailed discussion see *Study Design and Measurement Objectives*).

The third issue is the epoch setting, i.e. the aggregation level/period length used to analyze the raw acceleration. Aggregation into epochs is necessary to feed raw data into various prediction methods, whether they are equations or simple cut-points. Particularly in children, whose MB pattern is known to be spontaneous and intermittent, an epoch length between 1-5 seconds, or the shortest possible epoch length is recommended (Banda et al., 2016; Bornstein et al., 2011; Heil et al., 2012; Kettner et al., 2013; Migueles et al., 2017; Sigmund et al., 2014). In contrast, long epoch setting such as 60 seconds are known to underestimate MVPA in children (Guinhouya et al., 2013). Here it must be noted that with longer epoch lengths, short vigorous PA intervals are more often detected as moderate PA and short intervals of moderate PA are at the same time only detected as LPA. The accelerometer studies chose to use an EL of 60s due to the smaller storage capacities in the early years. With better storage capacities today, smaller EL are not a problem any more and highly recommended. The optimal epoch length in terms of health outcomes is as of yet unknown.

Context Information

Using diaries or questionnaires assessing the MB context is essential for specific research questions. For example, the simultaneous application of self-reports and device-based measurements enables to reliably quantify the volume/intensity of MB within a specific time frame such as working or school hours, and timing of organized sports (Helmerhorst et al., 2012; Reilly et al., 2008; Sprengeler et al., 2017; Westerterp, 2009). If schedules are available, this information can be gathered on groups' level in a less time-consuming manner, e.g. school classes (Sprengeler et al., 2019). If they are not available the use of wear-time-protocols or log-books needs to be considered (Burchartz et al., 2020). The combination of self-reports and device-based measures can enable a comprehensive understanding of MB (Sallis & Saelens, 2000). The accelerometer can only capture accelerations to create an activity profile about the frequency, intensity, and duration of the activity when it is worn, so detailed information about the activity type, quality and context is needed for a complete understanding of the MB assessed.

Non-wear time

Since most accelerometers are not waterproof (a few exceptions are the latest sensors from GENEActiv and Axivity), essential amounts of aquatic PA will not be measured. In this case or when the participants forget to wear the accelerometer, the non-wear-time must be identified (via self-report or algorithms). In general, algorithms for detecting non-wear times consist of time intervals with successive values of the lowest valid acceleration with or without a tolerance of several minutes in which small accelerations are allowed, with optional windows of zero acceleration before and after this tolerance. The algorithm of Barouni et al. (2020) additionally analysed respiration pattern to differentiate wear from nonwear time. Toftager et al. (2013) recommend that the different algorithms should be used only for the specific subgroups in which they have been validated. There are different algorithms for different age groups and more studies are needed to test the accuracy of each algorithm for these different age groups (Migueles et al., 2017).

The non-wear-time data need to be excluded from the data analysis or it will likely be categorized as SB. This introduces a bias as non-wear-time normally is associated with some kind of activity with an intensity higher than SB. As mentioned before 24-h movement recording require different methods of data analysis since during sleeping the movment is even lower than during SED (Chastin et al., 2015). When devices are not worn during sports activities, imputing

MVPA for the duration of sports activities should be considered with caution. It is highly unlikely that the entire duration is spend doing MVPA. It is not recommended to enter the complete time spent during a sport as MVPA as stated in the diary. An imputation of 50% of the reported duration is a good solution if the average PA value is to be analyzed from an epidemiological point of view, particularly in children (Fairclough & Stratton, 2006; Hollis et al., 2016; Sprengeler et al., 2019).

Compliance

Trained study staff should hand out the devices and motivate the participants to wear the device at all times. It is best if the participants are introduced how to wear the device correctly. Important points of wearing the accelerometer (placement, wearing times, data protection and return of the device) should be summarized in an information sheet to be handed out to the participants. In particular, concerns can be dispelled by pointing out that only an activity sensor (accelerometer) is present and used to detect MB (as opposed to camera, GPS, WLAN, Bluetooth or similar). In some countries, it is possible to get an ethics statement to collect GPS data – even for children, which provides rich data sets on MB.

In some sports, it is prohibited by the organizing association/organization to wear electronic devices for recording and real-time evaluation of activities. Additional information sheets with further information about the study for teachers, trainers, coaches, parents or employers, depending on the setting in which the study takes place, should be provided, too. This information may prevent the devices from having to be removed at sporting events or during work/school that would result in data loss. When returning the device per mail, an addressed and stamped envelope should be provided to the participants to make it as easy as possible for them to send it back. A follow-up protocol by telephone if the devices were not returned can be implemented (Burchartz et al., 2020). The already recommended 24h recording time can also increase compliance. On the one hand, it provides a comprehensive picture of activity during waking hours, sleep patterns and inactive phases. On the other hand, the compliance is better, as the participants do not have to pay attention to taking off the device at certain times (e.g. sleep).

Current developments in statistical analysis

Acknowledgement of the intrinsic co-dependency between human behaviors during a finite amount of time

The measurement of human behavior such as PA, SB and sleep with accelerometer devices results in data sets representing observations of a finite amount of time, e.g. 8h, 12h, 24h or 7 days. Within the observed time frame, the amount of an individual's behavior sum up to 100% and an increase in one behavior ultimately leads to a decrease in at least one of the other behaviors. These circumstances have important implications for interpreting the results from the statistics used and the interpretation of the results in relation to health benefits.

Standard procedures of multivariate statistical analyzes (e.g. linear regression, ANOVA) assume that time spent in one behavior is independent of the time spent in any other behavior and that the amounts are potentially infinite. However, accelerometry always deals with finite amounts of time and applying, for example, a standard linear regression technique may in some cases lead to multicollinearity issues. Over decades, research on human behavior in relation to health most often has not taken advantage of the inter-relationships between time-linked behaviors by examining the specific behavior of interest in isolation, rather than investigating the dependencies that do exist (Mekary et al., 2009). Recently, several research groups have worked on different strategies to acknowledge the co-dependency between behaviors, and to apply more sophisticated statistical approaches, such as Isotemporal Substitution Model (ISM), Compositional Data Analysis (CoDA), Multivariate Pattern Analysis or Bayesian Dirichlet distributions (Aadland et al., 2018; Chastin et al., 2015; Mekary & Ding, 2019; van der Merwe, 2018). In October 2019 an international workshop took place in Granada organized by Francisco Ortega with the focus on statistical methods to analyse accelerometer-measured physical activity. As a result of this workshop, there will be a detailed consensus paper on analytical approaches to assess associations with accelerometer-determined physical behavior in epidemiological studies. This will give an expert description and discussion of currently available statistical approaches to use in epidemiological studies as well as highlighting their strengths and limitations.

Isotemporal Substitution Model / Compositional Isotemporal Substitution Model

The ISM was originally developed by Mekary and colleagues (2009) to analyze data of SB and PA. The overall aim of the ISM is to estimate the effect of replacing one specific behavior with another behavior for the exact same amount of time. With a setup of different models, the association with a specific health outcome variable (e.g. BMI, biomarkers) for a predicted replacement of one behavior with another can be estimated. The ISM approach is able to control for all relevant behavior-related variables and the observed total time. It is important to note that in most cases, absent multiple measure of behavior over time, that the association only describes the predicted influence of changing behavior rather than the effect of an actual change.

Compositional Data Analysis

The CoDA approach was developed by Chastin and colleagues (2015) to analyze PA and SB data. CoDA accounts for the constraint structure of the data, namely the finite amount of time of e.g. 24h. Such data can only exist in a specific constraint geometric space, the so-called *simplex*, according to the Aitchison geometry (Aitchison, 1982). However, standard statistical techniques apply the Euclidean geometry and assume potentially infinite data. To analyze data of compositional nature, the data first has to be expressed as so-called isometric log ratios (ilr). Compositions of ilr-coordinates can then by analyzed in the Euclidean geometry with standard statistical techniques. CoDA can be applied with the aim to use the composition of human behaviors as an explanatory variable or to predict the change in specific health related outcome variables (e.g. BMI, biomarkers) in relation to behavior change. Dumuid and colleagues (2018) have recently developed and tested a compositional ISM in an empirical study.

Multivariate Pattern Analysis

Multivariate pattern analysis is widely used in pharmaceutical and metabolomics studies and has recently been adapted by Aadland et al., 2018 to analyze accelerometry-derived SB and PA data in relation to cardiometabolic health. Multivariate pattern analysis accounts for the multicollinearity of SB and PA data and provides a solution to analyze a more detailed spectrum of PA intensities in comparison to the established, but rather broad overall summary measures (e.g. SB, LPA and MVPA). Furthermore Aadland, Kvalheim et al., 2019b showed that the explained variance of metabolic health was tenfold when applying the full spectrum of PA intensities from three-axis in comparison to the traditional MVPA summary derived by counts per minute from the vertical axis only.

Bayesian Dirichlet distribution

For several research questions, it may be of interest that a composition of human behaviors such as SB and PA is the dependent variable. A Bayesian approach using a Dirichlet distribution is suggested (van der Merwe, 2018), which accounts for the compositional nature and allows for one or more independent variables in a regression model. As an empirical example, how player positions in team sports affect the amounts of standing, walking and running is examined - measured via accelerometry - during the game, which can be of great importance in sport science and practical coaching situations.

Practical suggestion

The research community has not yet reached a consensus on the most promising approach, and both, traditional isotemporal substitution models and compositional ISM, have tended to show broadly similar results (Dumuid, Stanford, Pedišić et al., 2018). Mekarey and Ding (2019) argue in their comment article in relation to a compositional ISM study by Biddle and colleagues (2018) that their original ISM has several advantages compared to the compositional ISM such as a straightforward interpretation and an intuitive articulation of the results with regard to PA guidelines. The original ISM uses absolute values of time spent in a specific behavior instead of relative values that are used in the Compositional ISM by Biddle et al. Biddle et al., 2018, Dumuid et al. (2018) and Fairclough et al. (2017). Aadland, Kvalheim et al., 2019a compared multiple linear regression, CoDA and multivariate pattern analysis in an empirical study. Substantial differences for the associations between PA intensities and cardiometabolic health were identified and the authors argue that multivariate pattern analysis should be considered in future studies.

Each approach has its strengths, limitations and practical relevance. Therefore, researchers must carefully inspect the approach that fits best to their research aim and data. Helpful guidelines for the analytical process are available: Mekary et al., 2009 provide detailed information regarding the applied substitutional model and other related models in the appendix; Chastin et al., 2015 provide detailed information regarding the compositional nature of sleep, SB and PA and Dumuid, Stanford, Pedišić et al., 2018 provide a description and sample R code in the Supplementary Material accompanied to the respective article. Aadland, Andersen et al., 2019 provide a tutorial that guides the reader on how to conduct multivariate pattern analysis with respect to PA and health. van der Merwe, 2018 also provides a description, sample R code as well as an example data set to adapt his Bayesian approach to handle compositional data in regression modelling.

It is important to note that the application of these statistical approaches is rather complex in comparison with standard procedures of multivariate statistical analyzes (e.g. linear regression, ANOVA). Researchers are therefore encouraged to seek advice from appropriate experts.

Future Directions

Algorithms for intensity detection and validation studies

Traditionally, the intensity of PA determined by accelerometers is determined by the accumulated number (the outcome metric, sometimes referred to as "counts") of threshold exceedances (so-called cut-points) per time unit (epoch length). The raw signals of the accelerations measured by the accelerometer are processed and evaluated by various methods. Various validation studies for across age groups and devices determine cut-point values for SB, light, moderate and vigorous intensities (Migueles et al., 2017; Schaefer et al., 2014). This has proven to be successful, as the intensities for different age groups and different target groups differ greatly from each other. Due to the large number of available devices, however, the number of intensity algorithms is also very high. So far, there are no uniform international standards that specify how validation studies should be conducted for the different target groups, so that the results calculated afterwards would be comparable. Relatedly, an unanswered question using epoch lengths is if and how measuring at smaller epochs affect estimates of PA minutes and meeting PA guidelines.

However, we recommend not using device-based outcome metrics anymore because it is not always known or reported how they are computed. Many commercially available devices keep these methods for count calculation proprietary. Newer device manufacturers (e.g. activpal, movisens, GENEActiv), mostly with a scientific background, have therefore increasingly opted for an open science approach, making comparability between devices possible. Future intensity calculation algorithms should be based on raw data from accelerometers and be open for the public. This open science approach would facilitate studies to compare their data with raw data from other studies by applying the different algorithms to their own raw data set.

This is why pattern recognition algorithms are emerging in the field right now. Due to the amount of raw data available for evaluation, different algorithms, for example from the field of speech recognition, are being tested in the last years to be used to find MB patterns in accelerometer data. Different studies and researcher like Farrahi et al. (2019), Smith et al. (2019) or the group around Stewart Trost (Ahmadi et al., 2019; Tong et al., 2019) are currently working on using supervised learning algorithms as well as deep learning and convolutional neural networks to predict activity patterns and energy expenditure from body worn accelerometers.

Sleep detection

As sleep is related to many health outcomes, future studies should also use the opportunities of accelerometers to assess different sleep outcomes, like sleep duration, sleeping habits including sleep movements, sleep-related health issues like apnea, or daytime naps. The differentiation of sleep and sedentary behavior can be difficult at times (e.g. the difference between lying on the couch watching TV and sleeping on the couch in front of the TV). An important point to consider is the positioning of the accelerometer. Positioning the sensor on the thigh makes it possible to detect different body positions very well. Smith et al (2019) validated different body placements of accelerometer and found that the hip may be superior for sleep timing and quantity metrics, whereas the wrist may be superior for sleep quality metrics. In the future more studies like the one by Barouni et al., 2020 are needed that differentiate between wake, sleep and nonwear periods. Studies that confirm the best placement for accelerometers during PA, SB and sleep like (Leppänen et al., 2019) are needed as well.

Timing of PA

Sleep/active cycles

Moreover, the inclusion of sleep pattern assessment can provide deeper insights into sleep/wake patterns of participants. After achievement of more accurate algorithms for sleep and daytime nap detection (potentially by inclusion of other sensors, or measuring heart-rate variability), gaining deeper insights into inter-individual daily routines and making it possible to more precisely determine the relationship between active and sedentary versus sleep times should be the focus of future research.

Activity throughout the day

Moreover, accelerometer use makes it possible to examine different activities regarding duration and intensity over the whole day (if the device is worn throughout the whole day). Using this data, researchers can make specific statements about when, for how long and in which intensity a person is active. Here, daily patterns can be examined, i.e. if someone is walking to work every day at the same time, or if someone has any activity routines. This also allows the investigation of within-day transfer or compensation effects of PA or SB.

Non-wear-time protocols via Ambulatory Assessment

The manual input of non-wear-time protocols to the PA data is too time consuming and distorts the device-based collected data set with subjective assessments of activity. A more sustainable approach is to use ambulatory assessment in combination with 24h recording. Triggered e-diaries can ask the subjects about activity right after certain events have been detected (device not worn, periods of high activity or SB). This means that non-wear times and especially reasons for that can also be recorded relatively precisely. This allows at least the recording of PA while the device was not worn and the participant can be given feedback on how much activity was not recorded as well as the activity type and context. Due to the continuous technical progress and the constantly decreasing size of the sensors, the simultaneous use of several sensors will be conceivable in the future. This could combine the advantages of different carrying positions and additionally improve the detection of certain MB (Reichert et al., this issue)

Smart Patches and Clothes

To encounter compliance problems and the difficulties in comparing data inter-individually due to different wear-times, body-mounted sensors, smart patches or smart clothes are promising attempts. This technology also has the potential to be used in automated activity profiling systems which produce a continuous record of activity patterns over extended periods of time (Preece et al., 2009). However, a 24-hour assessment faces multiple challenges: First, adherence of participants must be ensured. People are more likely to wear a monitoring device if it does not interfere with their daily habits and activities (Evenson et al., 2015). A hip-worn device, for example, is not feasible for tight clothes; a wrist-worn device is not suitable for a craftsperson wearing gloves, and either device is not suitable for a swimmer if it is not waterproof. A promising approach to encounter these issues is the establishment of more (validated) user-friendly equipment, like (waterproof) smart patches (Schneller et al., 2017). A microchip gathering tri-axial acceleration data (and possibly more) mounted in a small patch that can easily be adhered at any body location. The first commercial products (e.g. biobeat patch or Moio.care smart patch) are already on the market. At present, these products are still associated with high costs for individual smart patches. In addition, these devices can often only be used once or a limited number of times and must then be disposed which produces a lot of waste and is not as sustainable as reusable devices such as typical accelerometers. Reusable devices that are attached to the body with bio patches are preferable to one-use devices. Due to the technological development, the sensors and device sizes are getting smaller and smaller and are therefore easier to use. A promising approach into this direction has already been made by leading sports manufactures by inserting such microchips into sportswear (e.g. shirts like the Hexokin Smart Shirt, or shoes, like the Digitsole Smartshoe, or the Skiin smart underwear) which can be used more than once. But even smart clothes still have a very limited lifespan, moisture during washing and the strain on cables and sensors caused by movement limit the length of time they can be used. A potential future direction is developing sub-dermal accelerometer computer chip implants. The potential in terms of data collection is great; however, this does raise major ethical issues as subdermal microchips cannot easily be removed. This would limit human rights with respect to privacy and making them to “transparent humans” with no chance to escape a permanent (possible) observation through data gained within these chips.

Combining accelerometry with other PA assessment methods

To obtain more comprehensive pictures of PA, SB and sleep behavior it is recommended to integrate accelerometry with ecological momentary assessment (EMA). EMA is a reliable instrument to gain Big Data, allowing to make differentiated assumptions about peoples’ everyday lives due to high-resolution data points which can be obtained by
a) collecting data from large numbers of subjects using e.g. mobile phones and by
b) assessing a large number of different measures from subjects (e.g., GPS, heart rate, heart rate variability, electrodermal activity, context, etc.; Hesse et al., 2015; Hidalgo-Mazzei et al., 2016). Both approaches can help to understand real life settings in different ways and are valuable approaches in various science topics (Berger et al., 2017). A detailed discussion of this approach can be found in the Ambulatory Assessment Paper (Reichert et al., this issue).

Conclusion

Accelerometry is the “state-of-the-art” when it comes to device-based measurement of MB. The advantage of accelerometry is that it can collect dense data over a long period of time allowing a detailed examination of daily behavior. From this multidimensional data, a great number of metrics can be derived to capture and describe the unique aspects of MB.

Besides PA, SB and sleep are the most common behaviors being assessed. Various carrying positions and sensors are available for the different areas of application. The complex and dense data resulting from device-based measured MB as well as the various options regarding devices, data collection and data analysis can also be a challenge for researchers. In addition, the different approaches used in studies can lead to limited comparability and reproducibility of study results.

The numerous considerations mentioned lead to concluding that:

- A recording time of 24 hours per day is recommended for at least seven days (Migueles et al., 2017; Tudor-Locke et al., 2015);
- Consider existing validation studies when planning one's own studies and to document as many technical decisions as possible when recording and evaluating data to enable data comparison across studies;
- There is a critical need for better validation studies (phase III studies in the Keadle et al., 2019 Framework). They are needed to clarify questions about the accuracy of various prediction methods,
- Determine format and sampling frequency of acceleration data (a sampling frequency of 30 Hz normaly meets the Nyquist criterion) the recording time (a 24h recording of at least one complete week using the shortest possible epoch length (1s) is recommended) which can be converted to longer epoch lengths if needed,
- In addition to the accelerometer, assess the type of activity performed during non-wear time and reasons for non-wear of the devices for a complete understanding of the PA behavior assessed;
- There are algorithms that can determine non-wearing periods, but ecological momentary assessment (EMA) methods are endorsed to capture contextual information and activities during non-wearing periods as mentioned in (Reichert et al., this issue).

Accelerometer-based PA measures are often assumed accurate and to reflect actual PA behaviors. However, the values from accelerometers are still estimates and in the absence of satisfactory agreement with ground-truth gold standard measures of free-living PA should not be interpreted as ‘actual’ PA levels. The research community has not yet reached a consensus on the most promising approach in statistical analyses of accelerometer data, besides that the inherent multicollinearity within data based on human behavior during a finite amount of time should be carefully considered. Each approach has its strengths, limitations and practical relevance. Therefore, researchers must carefully inspect the approach that fits best with their research aim and data. We propose that researches choose their method based on the most valid approach for their given behavioral metric. From that perspective, the method chosen will dictate the device type and prediction algorithm.

In exercise psychology, accelerometry is a valuable tool for experimental and correlational research as well as for developing individualized training programs. Besides gaining information like duration, length and height and triaxial acceleration within a passed training session, accelerometer data is also used in post-match analyses in team sports. For (self-) observational purposes, accelerometer-based information can be helpful in two main areas focused by exercise psychology: in motivation of people to engage in any kind of exercise, or athletes; and in barrier management. Here, a combination of accelerometry with other features (like EMA, diaries) is expected to be the means of choice. Moreover, individual feedback methods can be used to enhance enjoyment of exercise or training.

The best practices section of this paper provides valuable information also for exercise psychologists and points to further literature to reach a fundamental understanding of accelerometer use in exercise psychology. It should be used as a starting point for exercise psychologists that consider the use of accelerometers. The future directions section shows opportunities for further research and especially ambulatory assessment shows great promise in the field of exercise psychology.

The goal of this report is to help the end-user of MB monitoring devices wade through sometimes excessive technical details of accelerometry to outline best practices in selecting and applying devices to quantify three major behavioral categories of common interest to the research community: PA, SB, and sleep. There are still many challenges, but we also have exciting developments ahead of us in the future. Together with the technical developments in sensors which will be even smaller and more accurate.

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Title: **Assessing Physical Behavior through Accelerometry – State of the Science, Best Practices and Future Directions**

Highlights

- 24h objective recording of physical activity in real life over a period of several days and weeks.
- Can easily be used in various applications like interventions, epidemiology and surveillance.
- Together with the technical developments in sensors (smaller, more accurate and longer recording, integrated in clothing) accelerometers can collect even more data to evaluate.

Declaration of interests

☒ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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