Applied Ergonomics 63 (2017) 41–52

Contents lists available at ScienceDirect

Applied Ergonomics

journal homepage: www.elsevier.com/locate/apergo

A practical guidance for assessments of sedentary behavior at work: A PEROSH initiative

Andreas Holtermann [m, *], Vera Schellewald [c, g], Svend Erik Mathiassen [e], Nidhi Gupta [m], Andrew Pinder [f], Anne Punakallio [d], Kaj Bo Veiersted [n], Britta Weber [g], Esa-Pekka Takala [d], Francesco Draicchio [h], Henrik Enquist [l], Kevin Desbrosses [i], Maria Peñahora García Sanz [j], Marzena Malińska [b], María Villar [j], Michael Wichtl [a], Michaela Strebl [a], Mikael Forsman [k], Sirpa Lusa [d], Tomasz Tokarski [b], Peter Hendriksen [m], Rolf Ellegast [g]

[a] Austrian Workers' Compensation Board (AUVA), Wien, Austria
[b] Central Institute for Labour Protection - National Research Institute (CIOP-PIB), Warszawa, Poland
[c] German Sport University Cologne (DSHS), Köln, Germany
[d] Finnish Institute of Occupational Health (FIOH), Helsinki, Finland
[e] University of Gävle, Gävle, Sweden
[f] HSE's Health & Safety Laboratory (HSL), Buxton, Derbyshire, United Kingdom
[g] Institute for Occupational Safety and Health of the German Social Accident Insurance (IFA), Sankt Augustin, Germany
[h] National Institute for Insurance Against Accidents at Work (INAIL), Rome, Italy
[i] French National Research and Safety Institute for the Prevention of Occupational Accidents and Diseases (INRS), Vandoeuvre Les Nancy, France
[j] Spanish National Institute for Safety and Hygiene at Work (INSHT), Madrid, Spain
[k] Karolinska Institutet (KI), Stockholm, Sweden
[l] Lund University, Skane Medical Services, Department of Laboratory Medicine, Occupational and Environmental Medicine, Lund, Sweden
[m] National Research Centre for the Working Environment (NRCWE), Copenhagen, Denmark
[n] National Institute of Occupational Health (STAMI), Oslo, Norway

ARTICLE INFO

Article history:
Received 18 November 2016
Received in revised form
23 March 2017
Accepted 24 March 2017

Keywords:
Sedentary work
Wearables
Guideline
Sitting
Technical
Measurements

ABSTRACT

Sedentary behavior is defined as sitting or lying with low energy expenditure. Humans in industrialized societies spend an increasing amount of time in sedentary behaviors every day. This has been associated with detrimental health outcomes. Despite a growing interest in the health effects of sedentary behavior at work, associations remain unclear, plausibly due to poor and diverse methods for assessing sedentary behavior. Thus, good practice guidance for researchers and practitioners on how to assess occupational sedentary behavior are needed.

The aim of this paper is to provide a practical guidance for practitioners and researchers on how to assess occupational sedentary behavior.

Ambulatory systems for use in field applications (wearables) are a promising approach for sedentary behavior assessment. Many different small-size consumer wearables, with long battery life and high data storage capacity are commercially available today. However, no stand-alone commercial system is able to assess sedentary behavior in accordance with its definition. The present paper offers decision support for practitioners and researchers in selecting wearables and data collection strategies for their purpose of study on sedentary behavior.

Valid and reliable assessment of occupational sedentary behavior is currently not easy. Several aspects need to be considered in the decision process on how to assess sedentary behavior. There is a need for development of a cheap and easily useable wearable for assessment of occupational sedentary behavior by researchers and practitioners.

1. Background

Sedentary behavior is defined as sitting or lying with low energy

* Corresponding author.
E-mail address: aho@nrcwe.dk (A. Holtermann).

http://dx.doi.org/10.1016/j.apergo.2017.03.012
0003-6870/

expenditure (SBRN, 2012). People in modern industrialized societies spend more and more time engaged in sedentary behaviors during the main domains of living, like working (e.g. when using computers), travelling (e.g. when driving a car) and during leisure (e.g. when watching television) (Chau et al., 2012; Church et al., 2011; Ng and Popkin, 2012; Aadahl et al., 2013).

Prospective studies have demonstrated a positive association between self-reported time spent sitting and chronic disease and all-cause mortality (Dunstan et al., 2010; Ford et al., 2010; Hu et al., 2001; Katzmarzyk et al., 2009; Patel et al., 2010; Schmid et al., 2015; Stamatakis et al., 2011; Warren et al., 2010; Wijndaele et al., 2011). A meta-analysis including nearly 600,000 adults showed a dose-response relationship between self-reported daily total sitting and all-cause mortality, with a 2% increase in all-cause mortality per hour spent sitting per day (Chau et al., 2013). Importantly, several studies have found such associations even after adjusting for the extent of moderate or vigorous physical activity (Hancox et al., 2004; Honda et al., 2014; Hu et al., 2003; Katzmarzyk et al., 2009; Raynor et al., 2006; Thorp et al., 2011). This indicates that much time spent seated infers a risk for health impairments irrespective of the level of physical activity.

A systematic review devoted to detrimental health effects of occupational sitting found limited evidence for an independent association with musculoskeletal pain, some forms of cancers, cardiovascular diseases, obesity indicators, diabetes and mortality (van Uffelen et al., 2010). One systematic review on predictors for neck and shoulder pain reported limited evidence for a positive association between occupational sitting and non-specific neck pain (McLean et al., 2010), while insufficient evidence was found by two other systematic reviews (da Costa and Vieira, 2010; Mayer et al., 2012). For different cancer types, meta-analyses have reported varying associations with self-reported occupational sitting time (Schmid and Leitzmann, 2014; Zhou et al., 2015). Prospective studies on self-reported occupational sitting and obesity also present mixed evidence. One found that BMI decreased with less occupational sitting for women, but not for men (Eriksen et al., 2015), while no association between occupational sitting and BMI was found in two other studies (Pinto Pereira and Power, 2013; Pulsford et al., 2013). Studies also find conflicting results concerning associations between self-reported occupational sitting and mortality (Chau et al., 2013; Pulsford et al., 2015; Stamatakis et al., 2013; van der Ploeg et al., 2015). Thus, it is not clear if spending large amounts of time in sedentary behavior at work is an independent risk factor for health impairments. Moreover, dose-response relationships and, hence, threshold values for occupational sedentary behavior with respect to health outcomes remain to be established.

A likely main reason for the conflicting results on associations between occupational sedentary behavior and health is that the available research is almost exclusively based on self-reported sitting time measured by questionnaires. The strength of questionnaires is their low cost and low burden of effort, both for the participant and for the researcher. Thus, it is feasible to use questionnaires to collect information from large populations. However, self-reported sedentary time at work has been shown to be both biased and imprecise (Gupta et al., 2016b; Koch et al., 2016; Kwak et al., 2011; Lagersted-Olsen et al., 2014), and is therefore generally regarded to have severe limitations when used in studies of occupational sedentary behavior.

Visual observation, either on-site or videotaped is another method for assessing sedentary behavior. Observational methods are still a common approach among researchers and practitioners for assessing body postures at work (Mathiassen et al., 2013) and have shown attractive properties in being valid and reasonably reliable when trained observers rate postures of large body parts (Takala et al., 2010). However, observations are generally time consuming and expensive per unit of working time observed (Trask et al., 2013, 2014, 2012), and they are therefore only feasible with relatively short assessment periods and limited population sizes. Observation-based methods are also associated with considerable uncertainty due to observers differing in ratings (Denis et al., 2000; Rezagholi et al., 2012). Visual observations at the workplace can also be challenging due to the logistic burden associated with data collection and ethical aspects (e.g. observing work with patients). Observations may also modify the behavior of the observed worker (observational bias).

Because of the imprecision and bias of self-reports, and the costs, limited feasibility and methodological uncertainty of observations, it is generally recommended to use objective technical instruments for assessing physical exposures such as sedentary behavior (Burdorf and van der Beek, 1999; Wells et al., 1997). Technical instruments are believed to be both valid and associated with minor error in use (Hansson et al., 2001). A wide variety of ambulatory, direct technical assessment systems for use in the field (wearables) are already commercially available. Available wearables utilize technologies such as accelerometry, pedometry, heart rate monitoring and indirect calorimetry (Tremblay et al., 2010). The on-going development of these technologies has led to miniaturization and greatly diminished costs, increasing the feasibility of assessing sedentary behavior objectively on larger populations in real-life settings, with minimal disturbance for the participants. However, despite the greatly increasing accessibility to commercially available wearables for assessing sedentary behavior, accompanied by an increasing use of wearables among researchers and practitioners, no current practical guidance is available on how to properly assess sedentary work using wearables. Therefore, the Partnership for European Research in Occupational Safety and Health (PEROSH, http://www.perosh.eu/) gathered a group of scientists from several European research institutions with the aim of developing a practically useful guidance for researchers and practitioners on how to assess occupational sedentary behavior. The initiative focused on wearables. Thus, laboratory-based or stationary systems, e. g. optoelectronic systems, which are not feasible for data collection in real and dynamic work environments, were not included.

1.1. Definition of sedentary behavior —what should be assessed?

Any assessment of some exposure needs to be based on a clear definition of that exposure. A current limitation in sedentary behavior research is the ambiguity among descriptions of “sedentary behavior” in the available literature. For example, a major dictionary describes sedentary as “doing or requiring much sitting” or “characterized by a lack of physical activity” (Merriam-Webster, 2016). Thus, a vague description may lead to divergences among both researchers and practitioners of how to assess and understand “sedentary behavior”.

A strict definition for sedentary behavior has therefore been proposed by a network of experts in the field; “*any waking behavior characterized by an energy expenditure* $\leq$ *1.5 METs while in a sitting or reclining posture*” (SBRN, 2012; Straker et al., 2016). Following this definition, sedentary behavior includes tasks or movements performed sitting or lying down, if just energy requirements are low. Thus, a complete assessment of sedentary behavior requires assessment of the two different components in its definition: *energy expenditure* and *body posture*.

Assessments of energy expenditure have mainly addressed physical activities (Ainsworth et al., 2011). Energy expenditure can be described in terms of the energy requirements during human motion relative to those when the body is at rest, measured in metabolic equivalent units (METs) (Ainsworth et al., 2011). Thus, a MET value of 1 is equal to the energy expenditure in a person at rest, and a MET value of 3 corresponds to an energy expenditure 3 times larger than at rest. Generally, physical activities have been separated into 4 categories based on their MET value as; minimal,[1] light, moderate and vigorous. In this classification, minimal physical activity is defined as ranging from 1.0 to 1.5 METs (including activities like lying down, sitting still and standing still), light physical activity is defined as activities requiring between 1.5 and 3.0 METs (including sitting and standing performing tasks with the upper body, and slow walking). Moderate physical activity is defined as ranging between 3 and 6 METs (normal walking, carrying light loads), and vigorous physical activity exceeds 6 METs (activities like fast walking, running and cycling) (Ainsworth et al., 2011; Dunstan et al., 2012; Pate et al., 2008; Straker et al., 2016).

Because of the relatively small absolute difference in energy expenditure between sitting and standing posture (Fountaine et al., 2016; Gibbs et al., 2016), assessment of energy expenditure only does not provide reliable information about the gross body posture. Therefore, assessing sedentary behavior also requires measurement of body posture. Conversely, wearables may be used to assess a multitude of body positions, as per their anatomical location. However, although identification of sitting or lying posture alone provides some crucial information on sedentary behavior, it is unable to obtain information about other bodily motions that could require considerable energy expenditure while sitting or lying. For example, crane operators and forklift drivers may perform upper body work during sitting requiring as much as 2.5 METs (Ainsworth et al., 2011). Other examples are hand and machine sewing while sitting, requiring 1.8 and 2.5 METs respectively (Ainsworth et al., 2011) or using a semi-recumbent elliptical work station (e.g. LifeBalance Station) which can lead to an energy expenditure between 2.4 METs (light physical activity) and 3.1 METs (moderate physical activity) (Botter et al., 2016).

In summary, valid and reliable assessments of sedentary behavior require measurements of both energy expenditure and body posture.

1.2. Characteristics of sedentary behavior — what should be assessed?

Daily duration of sedentary behavior is the metric normally used for considering health effects of sedentary behavior, and for assessing the need for interventions aimed at reducing it. Additionally, information on the domain in which the sedentary behavior takes place, like work, leisure or transportation is often collected via self-reported diary entries.

The time patterns of sedentary behavior can also be important for evaluating its health consequences. For example, time spent in continuous prolonged bouts of sedentary behavior may be more detrimental to health than the same duration spent in shorter bouts (Carson et al., 2014; Gupta et al., 2016a; Healy et al., 2008). Investigations of sedentary behavior should not only address daily duration of sedentary behavior, but even the durations of sedentary behavior periods, as well as the periods of non-sedentary behavior. Methods have been proposed for how to properly express the timeline of variables describing sedentary and non-sedentary behavior (Hallman et al., 2015; Straker et al., 2014; Toomingas et al., 2012).

Time spent in moderate and vigorous physical activity is well documented to have significant effects on health (Bauman and Craig, 2005; Nocon et al., 2008; Warburton et al., 2010), which along with body posture (e.g. standing) and behavior (e.g. standing still or walking) during periods of occupational non-sedentary behavior may modify the health effects of sedentariness *per se*. Thus, these metrics can also be important information when describing and evaluating the overall health consequences of sedentary behavior and interventions targeting sedentary behavior (Danquah et al., 2016; Straker et al., 2016).

Thus, wearables capable of capturing not only the total duration and the time pattern of sedentary behavior, but also the duration and pattern of other postures and movements, and of energy expenditures above 1.5 METs, can be relevant when assessing the need for interventions aimed at reducing sedentary behavior, as well as their effects on health.

2. How to select the best wearable for occupational sedentary behavior assessment?

A variety of wearables are available for sedentary behavior assessment. In the process of selecting the best instrument and assessment procedure in a specific occupational setting, researchers and practitioners need to take several factors into account. The great variety of commercially available wearables further complicates this process. Thus, to provide an overview, we propose a classification system of currently available types of wearables. Based on this classification system, a decision support is proposed for identifying the characteristics of the best suited wearable for a given study purpose.

2.1. Sensor technologies for sedentary behavior assessment

2.1.1. Postural and kinematic assessment

The currently most popular sensor technology for capturing human movement is the accelerometer. The majority of available accelerometers measure accelerations on three orthogonal spatial axes, and can assess static spatial body segment orientation based on gravity, as well as movements, as derived from the dynamic changes in acceleration. For assessment of body segment orientation, low pass filtering of the acceleration signal from a 3-axis accelerometer and deriving the angles for each axis with respect to the gravitational acceleration vector allows it to be used as an inclinometer, which can provide assessments of relatively invariant postures (Chastin and Granat, 2010; Godfrey et al., 2008; Hansson et al., 2001; Skotte et al., 2014). Accelerometers are, however, less suitable for accurate assessment of spatial orientation and movements of body segments during fast movements (Plamondon et al., 2007). Activity counts assessment differs with respect to the time resolution, e. g. counts per second, minute or cumulative daily counts. The acceleration signal can be transformed according to activity count thresholds to measure overall levels of physical activity or further transformed into energy expenditure via algorithms based on calibration of counts into results obtained by indirect calorimetry or doubly labelled water (Schneller et al., 2015; Strath et al., 2013). The accuracy of these assessments is highly dependent on the calibrated activities being representative of the activity of the monitored subject (Weber et al., 2009). Accelerometers are quite small, with low battery consumption, and can easily be integrated with other sensors. Therefore, they are generally unobtrusive to wear and very practicable to use in the field. However, the method for calculating counts differs between accelerometers due to the lack of an industrial standard for transformation of raw acceleration data (Strath et al., 2013). This presents a challenge for standardization and comparisons of counts obtained from different brands (Wijndaele et al., 2015). Furthermore, the

[1] “Minimal physical activity” has been termed “sedentary” by Ainsworth et al., 2011. However, this usage of sedentary does not match the described definition of sedentary behavior. Therefore, “minimal” is used to describe the lowest category of energy expenditure to avoid confusion.

estimated energy expenditure derived from count frequencies cannot discriminate between types of activities (e.g. walking, stair climbing and lawn mowing) (Lyden et al., 2012; Matthews, 2005).

For more accurate 3-dimensional kinematic field assessments of body segment orientations and movements, inertial measurement units (IMUs) that consist of 3-axis accelerometers, 3-axis gyroscopes and 3-axis magnetic field sensors (magnetometers) are required. By integrating information from these complementary sensor types, the limitation of each individual sensor type is compensated for, allowing multisensory fusion algorithms to precisely assess 3-dimentional orientations and movements (Faber et al., 2016; Roetenberg et al., 2007). For example, the accelerometer and magnetometer measurements are used to compensate for the angular velocity integration drift of the gyroscope signal with respect to the gravitational acceleration vector and to the magnetic north (heading) respectively (Rizun, 2008; Roetenberg et al., 2005). However, magnetic field disturbances in the work place should be considered when applying a magnetometer.

2.1.2. Cardiorespiratory assessments

There is a linear relationship between cardiorespiratory stress and energy expenditure, and thus with activity intensity (Strath et al., 2000). Heart rate (HR) can therefore be used to estimate energy expenditure, which complements the data of accelerometers, leading to an increased accuracy for assessing physical activity and sedentary behavior. Different principles are available for assessing HR, with electrical (electrocardiography, ECG) and optical (photoplethysmography, PPG; blood volume pulse, BVP) sensor technologies being the most commonly used (Alian and Shelley, 2014; McArdle et al., 2006). Electrical heart rate sensors detect the electrical signals which lead to contraction of the heart. The unique structure of this signal allows detection of each individual heartbeat, and thus a calculation of the heart rate (AHA, 2016). A 12-lead ECG is considered the gold-standard for non-invasive electrocardiographic assessment in clinical settings, while a portable 3-lead ECG Holter system can be applied in the field. Although the validity and accuracy of the assessments are high, the technique is susceptible to artifacts from physiologic or non-physiological factors like muscle activity, motion or poor contact between electrodes and the skin (Chase and Brady, 2000). Commercially available consumer wearables are often based on 1-lead or 2-lead ECG setups.

Optical heart rate sensors use integrated photodiodes which shine light onto the skin and captures the amount of reflected light. When the heart muscle contracts, blood is being pushed through the blood vessels which then dilate. Relaxation of the heart muscle leads to a reflux of the blood and a shrinkage of the blood vessels. The amount of reflected light will change over time, following the changes in the volume of the blood vessels, and this can be used to assess the heart rate (Allen, 2007; Tamura et al., 2014). These sensors can, in principle, be applied anywhere on the skin, allowing for great flexibility, and they are also cheap. Typical placements are at the wrist, the ear lobes or the fingertips. The main limitation of this technique is its sensitivity to movement artifacts (Couceiro et al., 2012) and skin texture. Due to the complexity of the optical heart rate sensor signal, it heavily relies on good data processing to isolate the blood volume pulse, meaning that generally optical heart sensors are regarded as less accurate than electrical heart rate sensors.

Conducting an open-circuit spirometry is the most precise way to analyze the intensity of physical activity based on the method of indirect calorimetry. By measuring and comparing the consumption of oxygen and the production of carbon dioxide during rest and steady-state exercise, the oxidation of macronutrients and therefore the production of chemical energy as Adenosine triphosphate (ATP) is estimated indirectly (McArdle et al., 2006). An ambulatory breath analyzer can be used in the field, but the mask and the tubing makes it less feasible for long term assessments. Moreover, initial calibration of the system in the laboratory before the transportation, or calibration directly in the field can be problematic and may lead to drifts over the data acquisition period (Macfarlane and Wong, 2012).

2.2. Overview of types and characteristics of wearables

Although wearables have a wide range of technical specifications, they have some principal characteristics in common. Nearly all of the current commercially available wearables are small and unobtrusive, and can be attached and initiated by the users themselves. As the wearables are intended to be worn throughout the day (some even at night) the sensors are most often covered by skin-friendly, synthetic materials and enclosed in small cases and often integrated in synthetic or textile bands. Based on the type of sensor embedded in the wearable, it assesses and provides output parameters of general physical activity and inactivity (e.g. number of steps, activity intensity, rest), energy expenditure, posture and body movements. The level of detail and complexity of the outputs from the wearables increase with the number, type and quality of sensors used to capture data.

Depending on the technical specifications of the wearable, data can be recorded in time resolutions from milliseconds to minutes. But, in order to be user-friendly almost all wearables only provide daily summaries of activity outcomes. Most of the commercially available products provide an App or an online dashboard where processed data are illustrated, and this is often also displayed on the device itself (e.g. Smartwatches, Activity tracker with a display). The ability to store data on the devices themselves also depend on the specifications of the wearable, ranging from real-time streaming, to mobile data loggers (e.g. a mobile phone) and storage of daily, weekly or monthly summary data. Access to raw data and download of spreadsheets or files are most often limited to wearables for scientific purpose, where further data processing is needed. Like the capacity to store the recorded data, the battery life is highly dependent on the technical specifications of the wearable.

2.3. Derivation of a categorization of wearables

As mentioned, wearables differ considerably in integrated sensor technology and general characteristics. Based on the type and number of sensors used, how the sensor is attached to the body, and the accuracy and complexity of output data, wearables can be classified into three overall categories (Fig. 1).

2.3.1. Category 1 wearables

All accelerometers can provide data on the general level of physical activity. However, the accuracy and possible transformation of data to specific information on sedentary behavior and physical activity depend on the placement of the sensors (Trost et al., 2005). Most wearables in Category 1 are accelerometers, typically worn as a wristband, less commonly on the hip, with recorded data being interpreted as overall physical activity of the whole body. Another option is placement of the accelerometer on the leg (e.g. at the thigh) which provides the possibility to differentiate between body postures like sitting, standing, walking, and cycling (Byrom et al., 2016; Chastin and Granat, 2010; Skotte et al., 2014).

Most Category 1 wearables calculate energy expenditure of the user by transforming the accelerometer raw data into counts, and then transforming the counts into kilocalories or METs (Strath et al., 2013). With just one accelerometer worn on the wrist or hip, the accuracy of the transformation can be poor, due to the effect of physical activity and movements performed by body segments not being included in the assessment (Weber et al., 2009). However, the accuracy can be improved by combining accelerometers with heart rate sensors integrated into the same wearable (Atkin et al., 2012). The most commonly used recent Category 1 wearables combine accelerometry with heart rate monitoring using an optical heart rate sensor (photoplethysmographic) in a housing worn on the wrist. However, this heart rate assessment technique can be distorted by arm movements and changes in the sensor placement, corrupting the sensor signal (Tamura et al., 2014).

2.3.2. Category 2 wearables

More accurate assessments of kinematic and physiological responses can be conducted using Category 2 wearables. Category 2 wearables consist of relatively few independently positioned accelerometers and physiological sensors for obtaining more accurate information of physical activity, energy expenditure, body postures and movements than with Category 1 wearables. For example, placement of multiple accelerometers on a specific body segment or on two connected body segments provide a more accurate assessment of body posture and energy expenditure than using a single accelerometer only. Moreover, integrating data from accelerometers with assessments of physiological variables like heart rate from electrical heart rate sensors may provide valid information on both energy expenditure and intensity of physical activity (Brage et al., 2005; Corder et al., 2005). As one example, the combination of chest belts assessing HR and activity tracker worn on the wrist including an accelerometer fall in this category. Integration of the sensors into “smart textiles” can ease attachment, positioning and wear of multiple sensors. However, smart textiles generally require a rather tight compression fit to create good skin contact to assure correct positioning and function of the sensors. This may limit feasibility in long term assessments.

2.3.3. Category 3 wearables

Category 3 wearables are comprised of multiple sensor systems developed to simultaneously assess physical activity, body segment orientations and movements, as well as energy expenditure in the field with accuracy similar to that obtained under laboratory conditions. Moreover, they are generally more expensive than Category 1 and 2 wearables, and primarily developed for research purpose. Accurate assessments of discrete movements of individual body segments, their spatial orientation and joint angles can be provided by integrated wearable multi-sensor IMU systems in the field. Due to the multiple sensors, these wearables require considerable time and effort to be correctly attached on the body, and may not be particularly comfortable for the participant. For optimal accuracy, the sensors need to be calibrated before use, and the raw data usually requires processing with advanced software. Thus, Category 3 systems rely on expert knowledge and require relatively large investments of resources.

2.4. Output parameters and level of recommendation for assessing sedentary behavior from the categories of wearables

In the evaluation of which wearable system to use for assessing sedentary behavior, the output parameters provided by the wearable are important to consider. Different sensor technologies implied in wearables of the categories provide various output parameters describing body posture, energy expenditure and physical activity. Table 1 gives an overview of the output parameters related to sedentary behavior and the level of recommendation for assessing sedentary behavior from the different wearable categories.

Overall, the complexity of the output variables, as well as their accuracy, increases from Category 1 to Category 3 wearables. The Category 1 wearables are limited by the fact that placement on only one body segment provides spatial orientation of that specific segment, and no other segments of the body. For example, when a wearable is placed on the wrist or on the thorax, movements of the legs cannot be assessed, and the wearable cannot differentiate between body postures like sitting and standing still. By placing it on the upper body, distinction between an upright or lying position is possible, but still, the movement of the lower body cannot be assessed. Thus, when two or more sensors are placed on a body segment or on different body segments in Category 2 and 3 wearables, more accurate assessment of the orientation and movements of the body and body segments can be made. If complex postures and movements of several body parts (e.g. twisting the upper body while kneeling) is of interest to assess, sensors need to be attached on several body segments and connected to each other (i.e. Category 3 wearables). Therefore, the accuracy in assessment of temporal patterns, including frequency of changes and variation of body postures and movements, increases with the number of sensors, the number of body segments with sensors attached, and the types of sensors used.

The most common output parameters from wearables are values describing the amount and intensity of physical activity. This is mainly estimated by interpreting kinematic or physiological parameters. A general kinematic output variable from all systems is number and frequency of steps. Placing sensors on the hip, trunk or thigh leads to a more precise measurement of steps than with sensors placed on the arm or wrist. However, brands of wearables differ in accuracy of step quantification (Lee et al., 2015), and the number or frequency of steps cannot be used alone to assess physical activity intensity or energy expenditure accurately (Marshall et al., 2009). Another measure of general level of physical activity is the physical activity intensity (PAI) or counts (Weber et al., 2009). PAI or counts are calculated by first high pass filtering of the acceleration signal and then averaging over time (Weber et al., 2007). Calculations are possible for any body part instrumented with an accelerometer. By combining several accelerometers and weighing the accelerometer signals, PAI or count values can therefore be calculated for body segments, body regions and the whole body (Weber et al., 2007). PAI can be an important measure for sedentary behavior assessment, because PAI values of body parts are significantly dependent on the performed tasks during seated work (Groenesteijn et al., 2012).

Additional assessments of physiological data, like heart rate and ventilation makes the estimation of activity intensity more accurate than just interpreting data derived from accelerometers (Butte et al., 2012). Like previously, the accuracy of the heart rate measurement increases from Category 1 to 2 wearables, especially because of factors like the placement of the sensors and time distribution of recordings. Output parameters of ventilation like the breathing rate and minute ventilation can be assessed with electrical sensors placed on the rib cage (Category 2 wearables). Otherwise, using a mobile spirometry and conducting a breathing gas analysis (Category 3 wearables) offers the whole range of parameters to assess pulmonary function (Wanger and Culver, 2016).

The intensity of physical activity with respect to human metabolism can be measured as energy expenditure (Levine, 2005). However, because energy expenditure depends on a variety of interacting factors it is a challenge to assess it accurately. Heart rate and activity counts calculated from accelerometer data have commonly been used to assess energy expenditure. The estimation of energy expenditure from heart rate and activity counts are predominantly based on the linear relationship between activity intensity, heart rate, and energy expenditure. However, this

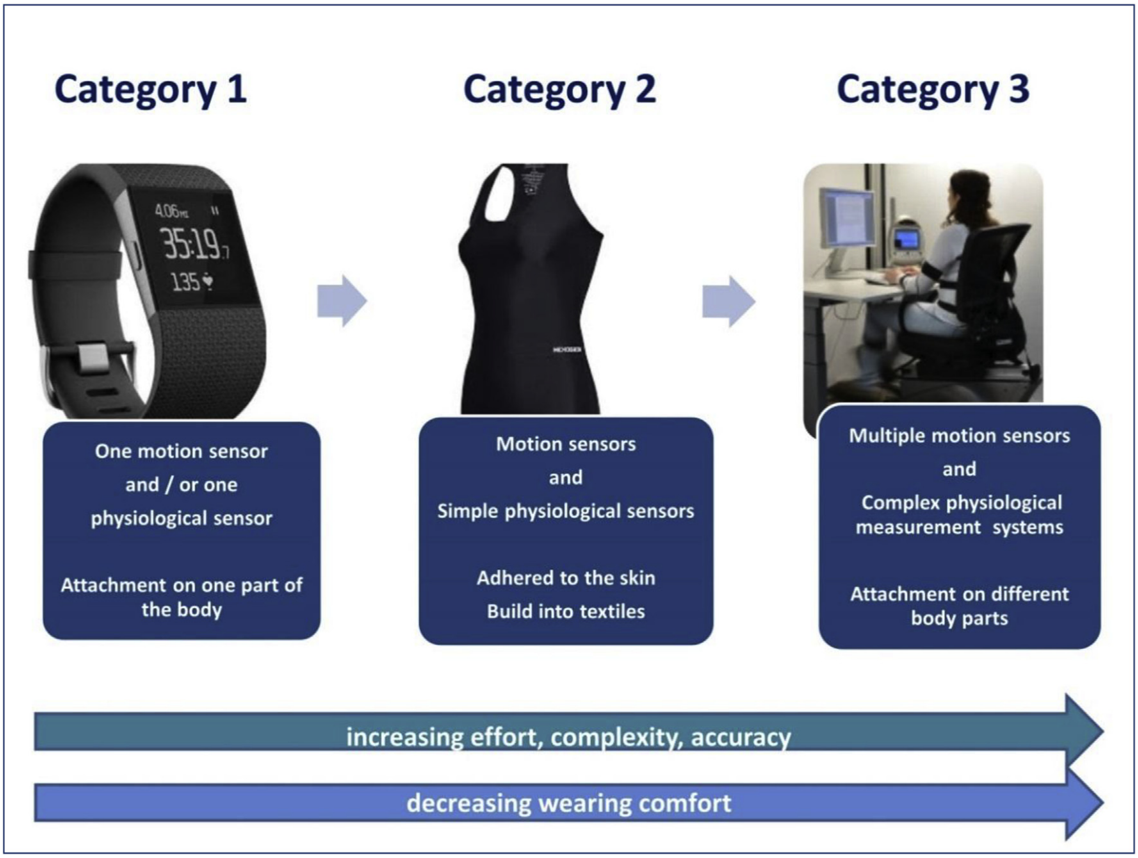

Fig. 1. Categorization of wearables based on type and number of sensors used, attachment of sensors on the body, and the accuracy and complexity of data assessed and provided.

linearity only holds true within a particular activity type (Schneller et al., 2015), making energy expenditure assessments more accurate when activity type also is assessed (Weber et al., 2007). All these output parameters cannot be assessed with Category 1 wearables, so accurate estimation of energy expenditure at least requires Category 2 wearables. The most precise manner to assess energy expenditure in the field is considered to be the indirect calorimetry (McArdle et al., 2006) by using a wearable breath analyzer, which is inherently a Category 3 wearable because of its low feasibility for field measurements and high requirements for calibration, data analyses and interpretations of output variables.

2.5. Overview of the main characteristics of the categories of wearables

The wide range of available wearables with different characteristics offers a variety of opportunities to assess sedentary behavior. Table 2 offers a decision support for choosing the best suited wearable for a particular study on sedentary behavior, depending on several factors, including accuracy, duration of measurements, and available budgets.

2.6. Data collection strategies

The preceding sections were devoted to identifying optimal instrumentation for assessing sedentary behavior, accommodaeting prerequisites such as validity, accuracy, feasibility, and budget. An equally important factor in determining the quality of the eventual result is the data collection strategy, i.e. the design of data sampling. Most often, this comes down to deciding for the number of subjects and number of days per subject in the eventual data set and, for data collections that do not cover full working days, the number of measurements per day (Liv et al., 2011; Mathiassen et al., 2002; Paquet et al., 2005).

Since not all subjects behave equally, and since not all working days look the same (Wahlstrom et al., 2010, 2016), results based on limited samples will inevitably be associated with uncertainty, or “random” error; as opposed to systematic errors, or bias, which may occur, for instance, if subjects or days are not representative for the population they are intended to typify. Also, the measurement instrument *per se* may contribute to the uncertainty of the eventual result, one example being that observers may differ considerably in their ratings of the same working postures (Dartt et al., 2009; Denis et al., 2000; Rezagholi et al., 2012; Trask et al., 2017). Wearable instrumentation for posture assessment is usually regarded as being associated with negligible random error in use (Hansson et al., 2001; Skotte et al., 2014), even though some technologies, such as accelerometers embedded in smart clothes, may show errors deserving consideration. Assessing uncertainty, typically expressed as a standard deviation or a confidence interval on the eventual result, is a key issue, both when examining the trustworthiness of any particular result and when designing a data collection to provide results of a pre-specified quality, such as in a standard statistical power analysis of studies intended to detect differences between groups, tasks or working conditions (Cohen, 1988).

The statistical performance of a data collection strategy, in terms of the precision of the eventual mean exposure value across all subjects and days, is directly related to the variability in exposure between and within subjects, and to the measurement effort in terms of the number of sampled subjects, days and measurements

Table 1
Overview of the output parameters and the level of recommendation for assessing sedentary behavior stratified on Categories of wearables.

Output parameters to assess sedentary behavior								
Wearable category	Category 1					Category 2		Category 3
Sensor types	Accelerometer + PPG or ECG					Accelerometer or IMU + ECG		IMU + ECG + indirect calorimetry
Attachment location	Single attachment on one body part					Attachments in one body region		Attachment on the whole body
Attachment(s)	Wrist/Upper arm	Chest/Back	Hip	Ankle	Thigh	Smart textiles	Few single sensors	Multi-sensor-systems
Output parameters								
Spatial orientation	Orientation of one individual body part					Orientation of one body region and few body parts		Orientation of several body parts, body regions and whole body
Activity type								
Sitting or standing	−	−	−	−	+	−	+	+
Upright or lying	−	+	o	o	+	+	+	+
Complex postures or activities	−	−	−	−	−	−	o	+
Activity intensity								
Steps	o	+	+	+	+	o	+	+
PAI calculation	PAI calculation for the instrumented body part					PAI calculation for one body region, few body parts		PAI calculation for body parts, body regions, whole body
Heart rate	o	+	−	−	−	+	+	+
Breathing	−	−	−	−	−	o	o	+
Energy expenditure estimation								
Low accuracy	+	+	+	+	+	+	o	−
Moderate accuracy	−	−	−	−	−	o	+	o
High accuracy	−	−	−	−	−	−	−	+

"+" recommended, "o" is partially recommended, "-" is not recommended; PPG = Photoplethysmography; ECG = Electrocardiography; IMU = Inertial Measurement Unit; PAI = Physical Activity Intensity.

per day (Samuels et al., 1985). Smaller variability and more samples lead to better precision, i.e. a result that is more likely to be close to the truth. Variability between subjects and days can be expressed in terms of variance components, which are individual sources of variability contributing to the overall dispersion (uncertainty) in data (Searle et al., 1992). Variance components can be extracted from a data set using standard statistical techniques such as ANOVA (Mathiassen et al., 2002) and REML-procedures (Liv et al., 2012), provided that multiple measurements are available on each level of interest, e.g. subjects and days. Some occupational studies have reported basic descriptive statistics on the variability between subjects in sitting time per day, if not separated into between- and within-subject sources of variability (Bennie et al., 2013, 2015; Hallman et al., 2016; Jans et al., 2007; Ryan et al., 2011; Toomingas et al., 2012). This data may give an idea about approximate sizes of overall variance in settings similar to those addressed by the studies. Since, however, between- and within-subject variabilities, even for a particular variable such as, e.g. percent time sitting, are grossly dependent on population and occupational setting, it is often advisable to conduct a pilot study to obtain study-specific variance component estimates prior to designing a full-scale data collection. This will help in arriving at a proper study design that will deliver results with a reasonable trustworthiness.

Well-established equations express the relationship between variance components and sample sizes, and the precision of the eventual result (Samuels et al., 1985). Based on these theoretical equations (Jackson et al., 2009; Mathiassen et al., 2002, 2003b), or on computer-intensive empirical simulation techniques (Burdorf and van Riel, 1996; Liv et al., 2011; Mathiassen and Paquet, 2010; Paquet et al., 2005), considerable research has been devoted to determining sufficient sample sizes for different purposes, different occupational exposure variables, and different occupational settings. However, little attention has been paid so far to the specific sampling needs in studies of sedentary behavior and physical activity assessed by accelerometry (Aadland and Ylvisåker, 2015; Pedersen et al., 2016). Calculations in these two cited papers were based on standard assumptions of data being normally distributed, but it has been questioned recently whether that assumption is valid for data on sedentary behavior. Most often, the occurrence of sitting, standing and physical activity is expressed in terms of percentages of time; explicitly or implicitly adding up to 100%. Data of this nature are "compositional" (Aitchison, 1986), and behave differently from data that are not constrained and do not add up to a constant sum, with consequences for sample size calculations and statistical testing. Future research will likely address sedentary behavior in this context, inspired by equivalent problems in other scientific areas (Filzmoser et al., 2009, 2010; Reimann et al., 2012). So far, however, only sporadic attention has been paid to the compositional nature of many variables addressing physical load (Chastin et al., 2015; Mathiassen et al., 2014).

As discussed above, the sample sizes necessary for obtaining a specified statistical performance, for instance in terms of the size of a confidence interval on an estimated group mean value of sitting time, strongly depend on the variability in sitting between and within subjects, which, in turn, depends on the occupational context. Thus, it is not warranted to issue explicit numeric guidelines on sample sizes, intended to be generally applicable to all studies of sedentary behavior. However, some decision support is provided by the generic equations expressing statistical precision as a function of variance components and sample sizes. Thus, these equations predict that a particular total sample size, for instance 50 measurement days, will always yield a better precision of the eventual mean value across samples if they are distributed "widely" among subjects (Samuels et al., 1985); collecting data for 1 day in each of 50 subjects leads to a better precision of the mean than collecting data for, e.g., 5 days in each of 10 subjects. The equations also convey that the marginal effect on precision of adding still another worker or day to a data set decreases with the size of the material. Thus, as an example, adding 5 workers to a data set that already contains 5 will decrease the variance of the mean to half its

Table 2
Overview of the main characteristics of the categories of wearables and recommendations for choosing a category of wearables to study sedentary behavior depending on its characteristics.

		Category 1	Category 2		Category 3
		Single attachment	Smart textile	few sensors	multiple sensor system
Output accuracy	low accuracy	+	+	−	−
	moderate accuracy	−	o	+	−
	high accuracy	−	−	−	+
Data accessibility	access to raw data very limited or not necessary	+	o	−	−
	limited access to raw data needed	−	+	+	−
	full access to raw data needed	−	−	o	+
Expertise in data analysis	not required	+	o	−	−
	partially required	+	+	o	−
	fully required	+	+	+	+
Measurement duration, battery economy	≤1 workday	+	+	+	+
	2-3 work days	+	o	o	−
	≥4 work days	+	o	−	−
Number of participants to be monitored	Few	+	+	+	+
	Moderate	+	+	o	o
	Many	+	o	−	−
Cost per participant	Low	+	−	−	−
	Moderate	+	+	o	−
	High	+	+	+	+
Attachment of measurement device	attachment with no specific requirements	+	o	−	−
	attachment with moderate requirements	−	+	o	−
	attachment with expert requirements	−	−	+	+

"+" is recommended, "o" is partially recommended, "-" is not recommended.

original size (SD reduced by 29.3%), while adding 5 workers on top of 15 will reduce variance by only 25% (SD by 13.4%). The theoretical equations are valid under a number of assumptions, including that data for different workers, days and measurements within days are independent. This may not be true, one example being that exposures close in time during a working day are likely correlated to a larger extent than exposures further apart (Liv et al., 2011; Mathiassen et al., 2003a). In case of correlation, more data are needed to arrive at a particular precision of the mean than predicted by the theoretical equations (Liv et al., 2011).

The discussion above addresses issues related to the statistical performance of data collection strategies, but it does not consider costs associated with sampling. Little research has been devoted to understanding and designing measurement strategies in the context of the basic trade-off between cost and precision, i.e. that more measurements lead to results of a better quality, but they are also more expensive (Mathiassen et al., 2013; Rezagholi and Mathiassen, 2010; Trask et al., 2014). This lack of evidence is surprising, considering that assessments of cost-efficiency are necessary to answer obvious questions such as "what is the cheapest possible strategy that can still produce information of a specified quality" and "which one of a number of alternative data collection strategies that entail the same cost leads to the better precision of the eventual result". Research into cost-efficient data collection is still in its infancy, let alone cost-efficiency studies of specific relevance to sedentary behavior and physical activity. However, generic equations are available for assessing the trade-off between cost and statistical performance in some study designs, including collecting data for a particular number of days and subjects (Mathiassen and Bolin, 2011). These equations show that the "rule" stated above of distributing a certain total number of measurements among as many subjects as possible to get the best statistical performance may no longer be valid if costs are also considered. Thus, if additional measurement days are cheap while additional subjects are expensive, while, at the same time, exposure variability between days is large compared to exposure variability between subjects; then, the best possible statistical precision at a specified total cost may be obtained with a data collection strategy directed towards many days per subject rather than many subjects.

Notably, the relative cost-efficiency of basic approaches in sedentary behavior research, i.e. questionnaires versus observation versus instrumentation, will change with the cost of applying these approaches (Trask et al., 2014). Since wearables are likely to get cheaper still, development will probably favor wearables, even from a cost-efficiency point of view. However, an intriguing alternative option is to predict data collected using wearables by models based on particularly cheap information, such as administrative records (Heiden et al., 2017). In some cases, such models may offer sufficient statistical performance to be attractive in terms of cost-efficiency. Some attempts have been made to develop exposure prediction models addressing sedentary behavior (Gupta et al., 2016b) and physical activity (Saint-Maurice et al., 2014), but so far with no emphasis on costs beyond anecdotal remarks. Considering the significance of designing data collection strategies for sedentary behavior and physical activity that can deliver sufficiently informative data at minimal cost, we emphasize this as a topical issue for future research.

3. Examples of using the guidance for selecting a wearable to assess sedentary behavior

In the following, we present four cases on how to use the guidance to select the best suited wearable to assess sedentary behavior. Case 1 and 2 presents the use of Category 1 wearables under specific conditions to allow for an estimation of sedentary behavior on a budget. Case 3 and 4 presents how to use the guidance to get the recommended assessment method for sedentary behavior in accordance with both intensity and posture.

3.1. Case 1 – evaluating sedentary behavior among office workers without sit-to-stand tables

A company considers buying sit-stand tables for their office workers. A practitioner is charged with a one week low-budget task of assessing the total duration of sedentary behavior at the office. Due to the low budget, correctly assessing both characteristics (intensity and posture) of sedentary behavior is not possible. Since sit-stand tables are not yet available, it can be assumed that all computer work is performed sitting at a low energy expenditure (i.e. only performing light or very-light upper body work). This analysis of the work situation, allows low physical activity intensity to be used as a reasonable proxy for sedentary behavior in this specific context. Allowing the practitioner to use a relatively cheap Category 1 wearable (capable of assessing physical activity intensity), to produce a rough estimate of the occupational sedentary behavior. However, these will include any low intensity standing behaviors during work. This could either be done with a single accelerometer on the hip or thigh, or a smartphone-based App. Because of a relatively homogeneous study population and work tasks performed on a day to day basis, a low intra- and inter-individual variability in sedentary behavior can be expected. Thus a reasonable precision of the eventual mean value of time in sedentary behavior across workers at the office can probably be obtained by relatively few measurements, distributed among as many workers as possible, and not necessarily for full days in each worker.

3.2. Case 2 – evaluating effects on sedentary behavior when introducing sit-stand tables among office workers

After having documented that the office workers on average spend 80–90% of their working time engaged in sedentary behavior, the practitioner is asked by the company to conduct a cheap and fast evaluation of the effect of introducing sit-stand tables on sedentary behavior. As in the previous case, the low budget does not allow for correctly assessing both characteristics (intensity and posture) of sedentary behavior. However, since both sitting and standing at the computer is expected to be low intensity work the practitioner can use a wearable that offers a valid assessment of total time spent sitting and standing to get a reasonable proxy estimation of sedentary behavior during work. To assess sitting time, the practitioner can use a Category 1 wearable capable of simple posture analysis, such as an accelerometer on the thigh (attached directly to the skin or fastened to a smart garment for easy positioning). Category 2 and 3 wearables would not be recommended because of the limited budget and time period available for data analysis. The practitioner can still expect a rather low intra- and inter-individual variance in the daily job task. However, a potential difference between workers in the acceptance of the introduced sit-stand tables might exist, and the use of the sit-stand tables might also differ throughout the working hours. Therefore the practitioner should carefully consider when, for how long and on how big a proportion of the workers he should assess to determine if the sit-stand tables are used based on the provided budget. If possible, conducting pilot assessments would be advisable.

3.3. Case 3 – assessing change in the time distribution of sedentary behavior

A researcher is concerned that initiatives at an office for reducing sedentary behavior could increase prolonged sedentary behavior or decrease physical activity during leisure among the workers, as this could potentially diminish the potential beneficial health effects of the reduced occupational sedentary behavior. To investigate this hypothesis, the researcher needs a wearable that can assess precisely the temporal distribution of sedentary behavior and physical activity intensity during work and leisure time, both before and after introduction of sit-stand tables. For this purpose, the wearable needs to be able to monitor both sitting and other postures, while simultaneously assessing energy expenditure. Thus, Category 1 systems will not fulfil the researcher's needs to determine both body posture and energy expenditure with a good accuracy. To detect the possible changes in sedentary behavior and physical activity during work and leisure time before and after the intervention, the wearable should be able to collect data continuously across several full days. With this requirement, Category 3 wearables and smart textile Category 2 wearables would not be useful. Thus, a Category 2 wearable directly attached to the skin would probably be the best choice of wearable for the study. Specifically, this study would require at least two synchronized sensors. Based on Table 1, two different wearable setups could be an option, i.e. 1) assessing posture by an accelerometer on the thigh, with a heart rate sensor for assessing energy expenditure, or 2) assessing both posture and total physical activity energy expenditure by using 3 accelerometers positioned on the thigh, trunk and upper arm respectively. As previously mentioned, this study would require assessments over several complete days on many workers to obtain sufficient statistical power for investigating the potential effects of reducing sedentary behavior at work on sedentary behavior and physical activity at leisure. Additionally a diary should be filled out by the participants on the time of starting and stopping work and sleep time to correctly allocate the measurements into work and leisure domain.

3.4. Case 4 – reducing sedentary behavior by increasing seated energy expenditure

A group of researchers wish to try and alleviate the detrimental effects of occupational sedentary behavior on the development of obesity amongst office workers. To investigate if sedentary behavior at an office could be reduced, as well as how much daily energy expenditure could be expected to increase by introducing an under-the-desk bicycle. To accomplish a valid and reliable assessment of the bicycle intervention on occupational sedentary behavior, the wearable should be able to assess energy expenditure, physical activity and a seated posture. Additionally we need to attribute an increase in energy expenditure to using the under-the-desk bicycle during seated activities; therefore assessing upper and lower body PAI would be beneficial. Due to the needed precision in energy expenditure assessments and the multiple body segment analysis of PAI, a highly accurate Category 3 wearable simultaneously assessing posture and physical activity intensity (PAI) by several accelerometers/IMUs and energy expenditure by an additional instrument would be needed. Posture, as well as upper and lower body PAI determination could be assessed by 3 or more accelerometers/IMUS, with at least 1 on the wrist/upper arm, 1 on the trunk, 1 on the thigh (with considerations to also instrument the lower leg/ankle). The energy expenditure could either be assessed by indirect calorimetry, using accelerometers/IMUs on the wrist/upper arm, trunk and thigh, or by a heart rate monitor. Due to the participant burden from the wearable instrumentation, maximum wear time of 4–8 h could be expected. The instrumentation and need for precision would pose relatively high requirements on correct positioning of the instruments, calibration, expertise and time available for data analysis. With the outlined high work load for each measurement and analysis, a relatively low amount of participants can be expected within a given budget.

4. Practical implications

This PEROSH initiative providing decision support for selecting ambulatory instruments (wearables) and data collection procedures when assessing occupational sedentary behavior was initiated on request from several European researchers and practitioners.

Current research on sedentary behavior using wearables is primarily based on activity counts from accelerometers worn on the wrist and hip. As previously described, these assessments can provide valid information on sedentary behavior under some specific circumstances, i.e. work without significant upper or lower body energy expenditure during sitting. However, for many occupational groups performing upper body work while sitting, such assessments will not be sufficient to obtain valid measures of occupational sedentary behavior. Thus, we recommend future research and practice to assess sedentary behavior in occupational settings in accordance with its definition (i.e. assessing both postures and energy expenditure).

Because of the great variety of available wearables that can be used to assess sedentary behavior, selecting the optimal instrument and the proper data collection strategy for a particular study purpose is not an easy task. We therefore recommend researchers and practitioners to use the proposed guidance, taking a variety of aspects into account in the consideration on how to assess sedentary behavior.

5. Summary

The increasing occurrence of occupational sedentary behavior in the industrialized world has received considerable attention because of its suspected negative health effects. However, associations between occupational sedentary behavior and health remain unclear. An important reason being, that assessments of sedentary behavior have been diverse and, in many cases, of poor validity and reliability.

Numerous small-size wearables for assessing sedentary behavior, with high battery and data storage capacity have become commercially available in recent years. However, no stand-alone commercial system can assess occupational sedentary behavior in accordance with its definition (i.e. a sitting or lying posture with low energy expenditure). Therefore, deciding on how to assess sedentary behavior is currently not easy.

This paper therefore provides decision support for researchers and practitioners aiming at assessing occupational sedentary behavior, in selecting useful wearables and a proper data collection strategy. The decision support emphasizes factors like the need for accuracy, study population, data accessibility, wearing comfort, expert knowledge for analyses, assessment duration, number of participants needed, budget available, and need for information on time patterns of sedentary and non-sedentary behavior, including moderate and vigorous physical activity. The need for assessing body posture, energy expenditure, or both, should be appraised based on the work tasks, target population and purpose of the study.

We emphasize the need for developing a cheap, feasible and easily useable wearable for valid and reliable assessment of sedentary behavior at work that can satisfy the needs of both researchers and practitioners. This may be feasible with an agreement between researchers and practitioners in how to measure sedentary behavior combined with the commercial interest in assessment of sedentary behavior and the fast development of measurement techniques.

Funding

This research is financially supported by the PEROSH institutions the authors are affiliated to. No specific grant from funding agencies in the public, commercial, or not-for-profit sectors were received.

Acknowledgments

We would like to thank the Partnership for European Research in Occupational Safety and Health (PEROSH, http://www.perosh.eu/) for initiating and supporting the study.

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